Journal of Current Multidisciplinary Research
(https://jcmr.journals.ekb.eg/)

Original Article

Received 18/10/2024
Accepted 19/01/2025
Published 27/01/2025

Skin disease classification: a comparison of Resnet50, Mobilenet, and Efficient-B0

Mahmoud Y. Shams[1], Esraa Hassan[1], Sara Gamil[1], Aya Ibrahim[1], Esraa Gabr[1], Sarah Gamal[1], Esraa Ibrahim[1], Fares Abbas[1], Ahmed Mohammed[1], Anwar Khamis[1] , Mohamed Hamed[1], Mahmoud Mokhtar[1], Roheet Bhatnagar[2]

[1] Faculty of Artificial Intelligence, Kafrelsheikh University, Kafrelsheikh 33516, Egypt

[2] Department of Computer Science and Engineering Manipal University Jaipur, Rajasthan, India.

***Corresponding Author**: Mahmoud Y. Shams, mahmoud.yasin@ai.kfs.edu.eg. ORCID: 0000-0003-3021-5902

Abstract

Background: Skin diseases are among the most common health issues worldwide, affecting mil-lions of individuals annually. Conditions such as Acne and Rosacea, Eczema, Exan-thems and Drug Eruptions, Scabies, Lyme Disease, Tinea and other fungal infections, and Vasculitis can significantly impact patients' quality of life. Early and accurate diagnosis is crucial for effective treatment and management. However, the diagnosis of skin diseases often requires specialized expertise, which may not be readily availa-ble in all healthcare settings. Misdiagnosis or delayed diagnosis can lead to inappro-priate treatments and worsening conditions. **Methods**: In this paper, we propose Deep Learning techniques for classifying six common skin diseases. Leveraging the DermNet da-taset, we utilized the EfficientNet-B0 model, known for its accuracy and efficiency, to categorize these dermatological conditions. Our methodology involved data aug-mentation, transfer learning, and fine-tuning the EfficientNet-B0 model. **Results**: The pro-posed approach achieved an impressive 99% accuracy on the validation set, demon-strating the potential of advanced convolutional neural networks for automated skin disease diagnosis. Furthermore, we compared EfficientNet-B0 with other popular models, including ResNet50 and MobileNet, revealing superior performance both in accuracy and computational efficiency. Specifically, the models achieved accuracy rates of 93%, 94%, and 99% for ResNet50, MobileNet, and EfficientNet-B0, respec-tively. **Conclusion**: These findings highlight the reliability and effectiveness of the proposed model compared to state-of-the-art approaches.Tumors have been rarely documented in the Arabian dromedary (*Camelus dromedarius*).

Keywords: Dermatological Conditions, Data Augmentation, EfficientNet-B0, Receiver Operating Characteristic.

1. Introduction

Dermatological conditions encompass a wide range of skin disorders that can affect individuals of all ages [1]. These conditions can have various causes, including genetic factors, infections, immune system dysfunctions, and environmental exposures. Accurate diagnosis and effective management are essential for improving patient outcomes. These skin infections are growing increasingly hazardous as time passes [2]. Professionals believe that if the problem is recognized early enough, it can be controlled. If a dermatologist employs manual approaches to identify problems, the situation may get more problematic. Figure 1 highlights the key elements of the image, including the different types of skin diseases. The main reason for many types of ailments. Furthermore, many skin disorders have identical visual appearances, thus physical diagnosis can be challenging [3]. we discuss several common dermatological conditions, including acne, rosacea, eczema, exanthems, drug eruptions, scabies, Lyme disease, infestations, bites, tinea, ringworm, candidiasis, other fungal infections, and vasculitis. The skin treatments are grouped in the following ways, such as eczema, which is diagnosed in many forms these days, such as creams, lotions, and ointments. The dataset consists of groups of images classified according to different categories of skin diseases. The classification challenges arise due to variations in the dataset's structure and the inherent complexities of the images. To address these issues, this paper utilizes a hybrid artificial neural approach, which combines deep learning, artificial intelligence, and machine learning techniques to improve classification accuracy. The proposed method incorporates image processing and data augmentation to mitigate overfitting. Features extracted after augmentation are then used as inputs to pretrained models, enhancing the robustness and performance of the classification system [4, 5]. We conduct three types of deep learning models, ResNet50, Mobile Net, and EfficientNet-B0, are loaded and compared to validate the method load module's universality. The experiment platform for the proposed real-time, customized, and extendable skin disease identification system is constructed. After comparison we found the EfficientNet-B0 model is the best, which is a comprehensive collection of dermatological pictures. EfficientNet-B0, a member of the Efficient Net family, is noted for its balance of performance and computational efficiency. To maximize the model's performance, we used significant data augmentation, transfer learning, and fine-tuning. We intend to demonstrate the model's ability to appropriately categorize diverse skin diseases and offer a detailed analysis of its performance measures. It tuned our model with 99% accuracy in validation, whereas Mobile Net decreased it with 94% accuracy in validation. ResNet50 achieved 93% validation accuracy. After evolution our model, we improve our model's performance even further by using Youden's J statistic and ROC curve analysis. A thorough understanding of the classifier's performance is offered by the ROC curve, which shows the True Positive Rate (sensitivity) versus the False Positive Rate (1-specificity) across a range of thresholds. The top-left corner of an ideal ROC curve indicates great sensitivity and a low false positive rate. To successfully balance sensitivity and specificity, Youden's J statistic enhances it by determining the threshold that maximizes the difference between the True Positive Rate and the False Positive Rate. The optimal categorization accuracy, minimizing errors and enhancing the reliability of our model in critical applications are ensured by the strategy.

1.1. Objectives

We describe a sophisticated dermatological diagnostic tool that intends to transform the way skin disorders are recognized and handled. Using cutting-edge technology, the program offers users with quick and precise examinations of numerous skin diseases. Individuals may quickly upload images of their skin issues and receive immediate feedback on probable diagnosis and advised next measures via an easy-to-use interface. The used technique not only saves time, but it also encourages proactive healthcare practices through early diagnosis and action. Users gain from accurate information that improves their awareness of skin health, allowing them to make more educated decisions regarding their health. Finally, the application aims to improve users' quality of life by providing quick access to individualized dermatological knowledge and assistance.

1.2. Research Gap

Automation in Dermatological Diagnosis: Traditional techniques of diagnosing skin illnesses rely mainly on dermatologists' manual inspection, which can be subjective and variable. The application of deep learning and artificial intelligence (AI) in automating skin disease categorization is a big step forward. However, the complexity and diversity of visual symptoms continue to provide a challenge in achieving consistently high accuracy across varied skin disorders.

Before systematic correction and robust validation, algorithms can harm patients, potentially raising ethical issues and thus requiring more stringent forward-looking scrutiny and regulation [6]. As a “black box,” the concept of deep learning is unknown at the stage, which may lead to unexpected system outputs. Moreover, even if the machine is inspired by humans, it is likely that humans may not fully understand how it works [7, 8]. Therefore, the acceptability of patient care using an opaque algorithm remains a moot point.

1.2. Motivation

The motivation behind advancing skin disease classification and detection lies in addressing critical challenges faced in dermatology, particularly concerning accuracy, accessibility, and efficiency as presented by Esteva et al. [6]. Moreover, the traditional diagnostic methods heavily rely on subjective visual inspection by dermatologists, which can lead to variability in diagnoses and delay in treatment [7]. The rising prevalence of skin disorders necessitates scalable and reliable diagnostic solutions [8]. Deep learning and artificial intelligence (AI) techniques offer promising avenues to automate and standardize the diagnostic process, thereby improving diagnostic accuracy and reducing the burden on healthcare providers [9].

Fig. 1: The different types of the most common skin diseases.

2. Related Works

Several scientists have proposed several image processing approaches based on deep learning for the detection of various skin conditions. In this regard, Shanthi et al. [10] present a novel convolutional neural network (CNN) architecture that identifies four selected classes such as acne, keratosis, Eczema herpeticum, and urticaria obtained from the Dermnet dataset and demonstrates that it can recognize skin conditions with an improved accuracy of 98.6% to 99.04%. Liao et al [11] provided a detailed CNN-based plan. The investigation takes use of sophisticated CNN architecture, including VGG-16, VGG-19, and GoogleNet. The experiment used two separate datasets, Dermnet and OLE, and the models' performance was compared. The ImageNet dataset was utilized to pretrain all the models. The VGG-16 model achieved top-5 accuracy of 91% on the DermNet dataset and 69.5% on the OLE dataset. Srinivasu et al. [12] utilized MobileNet V2 and LSTM to detect skin diseases by utilizing the HAM10000 dataset, which has a stated accuracy of 85%. They've also created an online application that classifies skin reductions. Employed SVM and

Random Forest to classify skin diseases using the Dermnet dataset, achieving an accuracy of approximately 85% [13]. We demonstrated the potential of deep learning for practical diagnosis utilizing huge datasets by automating the classification of skin diseases using 1300 images from the Dermofit Image Library using CNNs and Inception v3 models.Kawahara et al. and Esteva et al. demonstrated the potential of deep learning for practical diagnosis utilizing huge datasets by automating the classification of skin diseases using 1300 images from the Dermofit Image Library using CNNs and Inception v3 models.

3. Research Methodology

The proposed system is designed to classify six specific classes of dermatological conditions using advanced deep learning techniques. To evaluate performance, the classifiers were assessed based on both all features and specific features independently. Data augmentation was applied to mitigate overfitting, followed by feature selection to identify the most impactful attributes that enhance classification accuracy. These selected features were then used to improve the classification process and pinpoint critical factors influencing class discovery. The system employs well-known deep learning models to categorize the features into distinct groups. The approach consists of six phases: data collection, preprocessing, data splitting, feature selection, classification using pretrained models, and performance evaluation. The framework is applied to predict six common skin diseases, including Acne and Rosacea, Eczema, Exanthems and Drug Eruptions, Scabies, Lyme Disease and other infestations, Tinea and other fungal infections, and Vasculitis.

3.1. Data Set

We used a subset of the Dement dataset, focusing on six types of dermatological conditions: acne and rosacea photos, eczema photos, exanthems and drug eruptions, scabies, Lyme disease, and other infestations and bites, tinea, ringworm, candidiasis, and other fungal infections, and vascular disease images as shown in Table 1 and Figure 2. This dataset improves diagnosis accuracy and knowledge of dermatological illnesses by using a large collection of photos. Our strategy entails employing complicated deep learning techniques to construct robust models capable of categorizing these diseases, which might possibly aid dermatologists in clinical decision-making.

Fig. 2: Dataset Samples

3.2. Data Processing

The dataset images were obtained from various sources, they varied in format and size, making them unsuitable for predictive analytics. To standardize the data, all images were resized to a consistent shape of 224×224×3, incorporating row, column, and channel information, and stored in a 3D multichannel array that illustrated in Table 1.

Table 1. The dataset description and samples numbers

Condition Category	Number of Images
Acne and Rosacea	540
Eczema	511
Exanthems and Drug Eruptions	402
Scabies, Lyme Disease, and other infestations and bites	388
Tinea, Ringworm, Candidiasis, and other fungal infections	1,300
Vasculitis	415

3.3. Data Analysis and Visualization

To extract valuable insights and make well-informed judgments, it is essential to comprehend the attributes and features of picture data. Using a variety of Python tools, including pandas, numpy, sea-born, os, cv2, and matplotlib.pyplot, we explore the properties of picture data. By using matplotlib.pyplot, we can generate a bar chart that visually represents images across categories. Finding any class imbalances or variances in our dataset is made simple, which shows the number of images in each subdirectory that illustrated in Table 2. This representation aids in our comprehension of the structure of the dataset and can direct our choices in further investigation.

Table 2. The general dataset splitting.

Skin Disease	Training	Validation	Testing
Acne and Rosacea	3780	756	151
Eczema	3577	715	143
Exanthems and Drug Eruptions	3618	723	144
Scabies Lyme Disease and other Infestations and Bites	3492	698	139
Tinea Ringworm Candidiasis and other Fungal Infections	3900	780	156
Vasculitis	3735	747	149

3.4. Data Augmentation

Data augmentation improves model generalization and resilience by artificially increasing the training dataset by transformations such as zooming, flipping, and shifting. This variety decreases overfitting and enhances the model's capacity to deal with real-world unpredictability. As a result, the model performs better with fresh, previously unknown data. As a result, the dataset without augmentation has 3,556 images, while a new enhanced dataset with 14,990 shots of illness regions was created using augmentation techniques.

3.5. Label Encoding

Labels are 6 different classes of skin disease from 1 to 6. The labels are Acne and Rosacea, Eczema, Exanthems and Drug Eruptions, Scabies Lyme Disease and other Infestations and Bites, Tinea Ringworm Candidiasis and other Fungal Infection, Vasculitis.

3.6. Feature Extraction

The feature extraction utilized CNN architectures based on ResNet50, MobileNet, and EfficientNet-B0. The training phase in the proposed model encompasses deep feature extraction, while the subsequent testing phase evaluates the performance of these features when diagnosing new images [14]. The strength of deep learning models lies in their multi-layered structure for feature extraction to take place inside the CNN's convolutional layers, each of which serves as a specialized filter to extract distinguishing characteristics. Combining ResNet50, MobileNet, and EfficientNet-B0 for feature extraction ensures a comprehensive analysis of various attributes in the skin images. ResNet50, known for its ability to handle deep networks and avoid vanishing gradient problems, is complemented by MobileNet's efficiency and lightweight structure, as well as EfficientNet-B0's balance between performance and computational efficiency. The network gains the ability to extract hierarchical representations of features from the skin images as they go through these coupled layers, providing a more sophisticated understanding of the nuances associated with different skin disorders. The accuracy and reliability of the skin disease detection system are enhanced by the model's ability to discern minute visual cues that are indicative of skin disease.

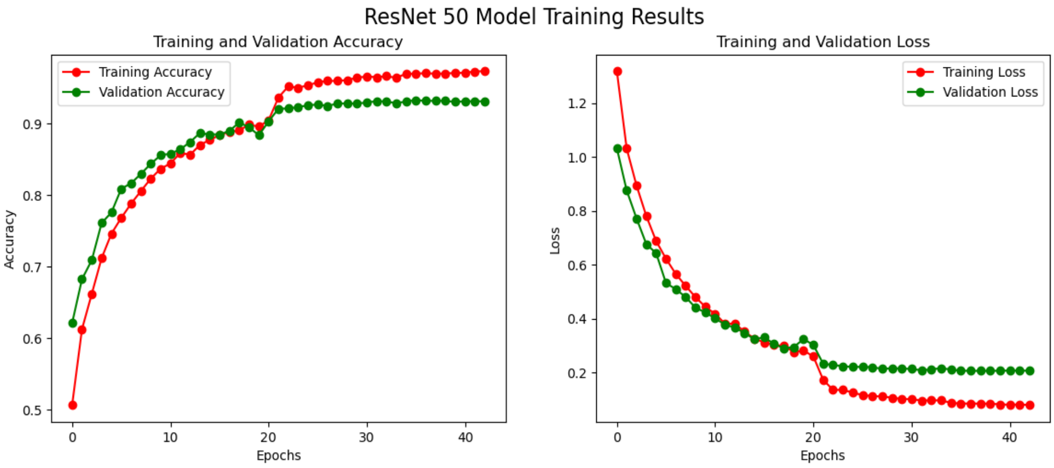
4. Evaluation Results

4.1. Model Implementation

In our approach, we utilized various state-of-the-art Deep Neural Network (DNN) architectures including ResNet50, MobileNet, and EfficientNet-B0 [15]. For each architecture, we employed the Keras Sequential API, incrementally adding layers starting with the input. These models, pre-trained on ImageNet, were fine-tuned on our dermatology dataset to leverage the benefits of transfer learning. For the ResNet50 model [16], we began by loading the base model pre-trained on ImageNet with the top layers removed. The base model's output was passed through a Global Average Pooling layer, followed by a Dense layer with 512 neurons and ReLU activation. A Dropout layer with a rate of 0.5 was added to prevent overfitting, and the final Dense layer used a SoftMax activation function to output the probabilities for each of the six classes. The model was compiled using the Adam optimizer with a learning rate of 0.001, categorical cross-entropy loss function, and accuracy as the metric. The MobileNet model followed a similar approach. The base MobileNet model, pre-trained on ImageNet, was loaded with the top layers removed. We added a Global Average Pooling layer, followed by Dense layers with 64 and 128 neurons respectively, using ReLU activation [17]. A Dropout layer with a rate of 0.5 was included to mitigate overfitting, and the final Dense layer with SoftMax activation output the class probabilities. The model was compiled with the Adam optimizer, a learning rate of 0.001, and categorical cross-entropy loss. For the EfficientNet-B0 model, we used a similar process. The pre-trained EfficientNet-B0 model, without the top layers, was loaded and its output passed through a Global Average Pooling layer. A Dropout layer with a rate of 0.5 followed, and the final Dense layer with SoftMax activation provided the class probabilities [18]. The model was also compiled using the Adam optimizer, categorical cross-entropy loss, and accuracy as the evaluation metric. To enhance the training process, we utilized callbacks including ModelCheckpoint to save the best model based on validation loss, ReduceLROnPlateau to reduce the learning rate when the validation loss plateaued, and EarlyStopping to stop training early if the validation loss did not improve. Each model was trained on the dataset with a set number of epochs, batch size, and using these callbacks to ensure optimal performance and generalization. By comparing these advanced architectures and employing rigorous training and validation strategies, we discovered that EfficientB0 model achieved high accuracy and reliability in classifying various dermatological condition.

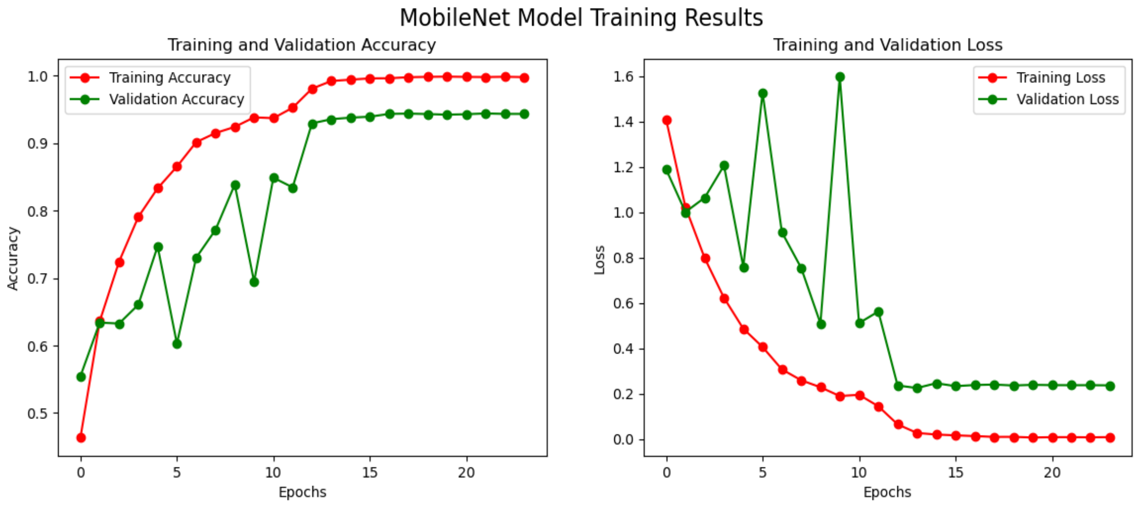
4.2. Model Results

Figure 3 displays two plots illustrating the training and validation accuracy and loss of a ResNet 50 model over 40 epochs. The red line with dots shows the model's training accuracy, which steadily increases from around 0.55 to nearly 0.95, with a slight plateau towards the end, indicating that the model is learning to classify the training examples increasingly well. The green line with dots represents the model's validation accuracy, also showing an upward trend, reaching approximately 0.9 but with a less steep slope and leveling off earlier than the training accuracy, suggesting that the model's performance on unseen data is improving but might be starting to overfit to the training data. The training loss, depicted by the red line with dots, decreases significantly from around 1.2 to approximately 0.2, indicating that the model's errors are reducing. The green line with dots shows the validation loss, which also decreases initially but plateaus at a higher level than the training loss, around 0.3, corroborating the overfitting observation from the accuracy plot. The ResNet 50 model demonstrates good learning behavior during the initial epochs, with both training and validation accuracy increasing and loss decreasing [19]. However, towards the later epochs, signs of overfitting become apparent: the training accuracy continues to rise steeply, while the validation accuracy plateaus; the training loss continues to decrease, but the validation loss levels off at a higher value to suggest that the model is memorizing the training data too well and might not generalize well to new, unseen data. To address potential overfitting, consider strategies such as early stopping when the validation loss starts to increase consistently, introducing regularization techniques like L1/L2 regularization or dropout, increasing the diversity of the training data through data augmentation, and experimenting with different learning rates, batch sizes, and optimizer configurations In the same Manner Figures 4 and 5 investigated the training, validation accuracy and loss in MobileNet, and EfficientNet-B0, respectively



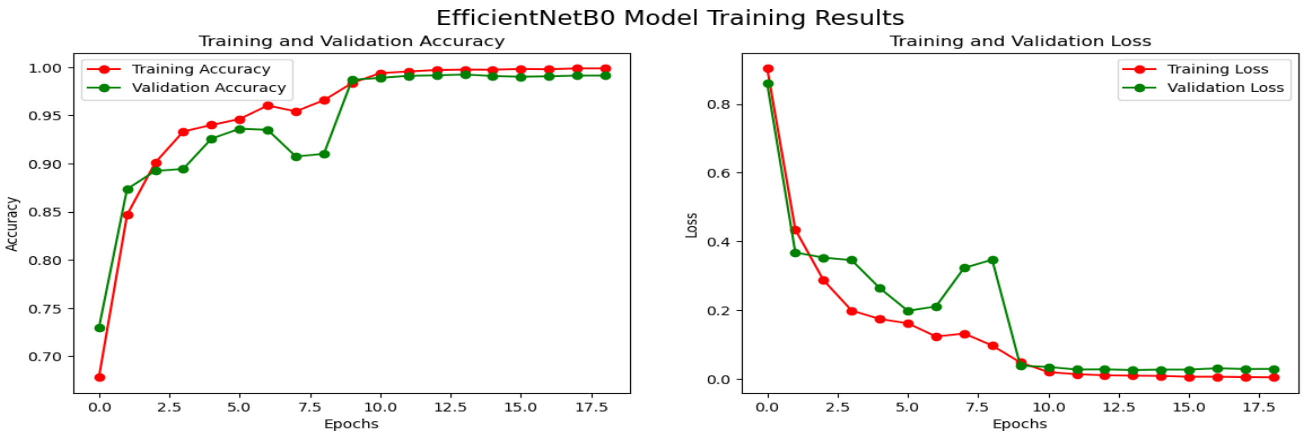
(a) (b)

Fig. 3: ResNet50 Model Results (a) ResNet50 Training and Validation Accuracy, (b) ResNet50 Training and Validation Loss.



(a) (b)

Fig. 4: MobileNet Model Results (a) MobileNet Training and Validation Accuracy, (b) MobileNet Training and Validation Loss.



(a) (b)

Fig. 5: EfficientNet-B0 Model Results (a) EfficientNet-B0 Training and Validation Accuracy, (b) EfficientNet-B0 Training and Validation Loss.

4.3. Evaluation Metrics

To evaluate CNN model performance are used by measuring the performance of the system we calculate precision, recall, F-score, and accuracy by following Equations (1-4). These metrics collectively provide a comprehensive assessment of the model's predictive efficacy as shown in Table 3.

$$Accuracy = (TP + TN) /(TP+TN+FP+FN) \quad (1)$$

$$P = TP / (TP+FP) \quad (2)$$

$$R = TP / (TP+FN) \quad (3)$$

$$F1\text{-}Score= 2*(P * R)/(P + R) \quad (4)$$

where TP represents True Positive, FP represents False Positive, TN represents True Negative and FN represents False Negative. Similarly, P, R represents precision and recall respectively [20–22].

Table 3. The results Resent the Confusion Matrix for each model**.**

	Accuracy	Precision	Recall	F1-Score
ResNet50	0.93	0.93	0.93	0.93
MobileNet	0.94	0.94	0.94	0.94
EfficientB0	0.99	0.99	0.99	0.98

4.4. Prediction

Using EfficientNet-B0 for High-Efficiency Prediction and ROC Analysis to Address False Positive Issues in Image Recognition. Medical and emergency situations rely heavily on accurate picture identification. False positive identifications, in which images without burns are wrongly identified as positive, can result in costly and serious mistakes. We used the EfficientNet-B0 model's efficiency and accuracy, as well as ROC curve analysis and Youden's J statistic, to establish the best thresholds for each class, therefore improving classification accuracy and lowering mistakes. Youden's J statistic was computed for each threshold to identify the optimal point that maximizes the difference between the true positive rate (TPR) and the false positive rate (FPR). To evaluate performance, Youden's J statistic, the area under the curve (AUC), and receiver operating characteristic (ROC) curves were utilized, as illustrated in Figure 6. These metrics provide valuable insights into the balance between sensitivity and specificity, aiding in the selection of the most appropriate classification threshold.

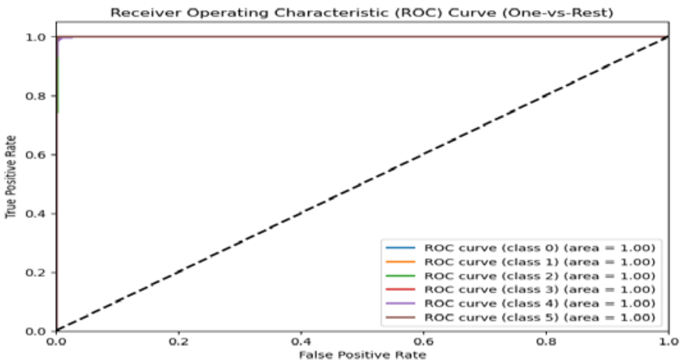


Fig. 6: ROC Curve for classes after use EfficientB0 Model

5. Conclusion and Future Work

In this paper, we present an advanced deep learning-based approach for the classification of six common dermatological conditions, employing the EfficientNet-B0 model. The study leveraged data augmentation, transfer learning, and model fine-tuning techniques to enhance classification accuracy and efficiency. Our experiments demonstrated that the EfficientNet-B0 model outperformed other models such as ResNet50 and MobileNet, achieving a remarkable 99% accuracy on the validation set. The use of ROC curve analysis and Youden's J statistic further optimized the model's performance by establishing ideal classification thresholds, thereby minimizing false positives. This sophisticated diagnostic tool not only improves diagnostic accuracy but also provides rapid and reliable assessments of skin conditions, potentially aiding dermatologists in clinical decision-making and improving patient outcomes.

Conflict of interest

The authors declare that they have no conflict of interest.

Authors' contribution

All authors are equally contributed and all authors read and approved the final manuscript.

References

1. Ferreira, I. G., Weber, M. B., & Bonamigo, R. R. (2021). History of dermatology: the study of skin diseases over the centuries. *Anais Brasileiros de Dermatologia*, *96*(3), 332–345. https://doi.org/10.1016/j.abd.2020.09.006
2. Clebak, K. T., & Malone, M. A. (2018). Skin Infections. *Primary Care: Clinics in Office Practice*, *45*(3), 433–454. https://doi.org/10.1016/j.pop.2018.05.004
3. Karthik, R., Vaichole, T. S., Kulkarni, S. K., Yadav, O., & Khan, F. (2022). Eff2Net: An efficient channel attention-based convolutional neural network for skin disease classification. *Biomedical Signal Processing and Control*, *73*, 103406. https://doi.org/10.1016/j.bspc.2021.103406
4. Verma, S., Razzaque, M. A., Sangtongdee, U., Arpnikanondt, C., Tassaneetrithep, B., & Hossain, A. (2021). Digital Diagnosis of Hand, Foot, and Mouth Disease Using Hybrid Deep Neural Networks. *IEEE Access*, *9*, 143481–143494. https://doi.org/10.1109/ACCESS.2021.3120199
5. Khan, M. A., Sharif, M., Akram, T., Damaševičius, R., & Maskeliūnas, R. (2021). Skin Lesion Segmentation and Multiclass Classification Using Deep Learning Features and Improved Moth Flame Optimization. *Diagnostics*, *11*(5), 811. https://doi.org/10.3390/diagnostics11050811
6. Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, *542*(7639), 115–118. https://doi.org/10.1038/nature21056
7. Rinner, C., Kittler, H., Rosendahl, C., & Tschandl, P. (2020). Analysis of Collective Human Intelligence for Diagnosis of Pigmented Skin Lesions Harnessed by Gamification Via a Web-Based Training Platform: Simulation Reader Study. *Journal of Medical Internet Research*, *22*(1), e15597. https://doi.org/10.2196/15597
8. Codella, N. C. F., Gutman, D., Celebi, M. E., Helba, B., Marchetti, M. A., Dusza, S. W., … Halpern, A. (2018, January 8). Skin Lesion Analysis Toward Melanoma Detection: A

Challenge at the 2017 International Symposium on Biomedical Imaging (ISBI), Hosted by the International Skin Imaging Collaboration (ISIC). arXiv. https://doi.org/10.48550/arXiv.1710.05006

9. Han, S. S., Kim, M. S., Lim, W., Park, G. H., Park, I., & Chang, S. E. (2018). Classification of the Clinical Images for Benign and Malignant Cutaneous Tumors Using a Deep Learning Algorithm. *Journal of Investigative Dermatology*, *138*(7), 1529–1538. https://doi.org/10.1016/j.jid.2018.01.028
10. Shanthi, T., Sabeenian, R. S., & Anand, R. (2020). Automatic diagnosis of skin diseases using convolution neural network. *Microprocessors and Microsystems*, *76*, 103074. https://doi.org/10.1016/j.micpro.2020.103074
11. Liao, H. (2016). A deep learning approach to universal skin disease classification. *University of Rochester Department of Computer Science, CSC*.
12. Srinivasu, P. N., SivaSai, J. G., Ijaz, M. F., Bhoi, A. K., Kim, W., & Kang, J. J. (2021). Classification of Skin Disease Using Deep Learning Neural Networks with MobileNet V2 and LSTM. *Sensors*, *21*(8), 2852. https://doi.org/10.3390/s21082852
13. Abdullah, A., Siddique, A., Shaukat, K., & Jan, T. (2024). An Intelligent Mechanism to Detect Multi-Factor Skin Cancer. *Diagnostics*, *14*(13), 1359. https://doi.org/10.3390/diagnostics14131359
14. Hassan, E., El-Rashidy, N., & Talaa, M. (2022). mask R-CNN models. *Nile Journal of Communication and Computer Science*, *3*(1), 17–27.
15. Shams, M. Y., Elshewey, A. M., El-kenawy, E.-S. M., Ibrahim, A., Talaat, F. M., & Tarek, Z. (2023). Water quality prediction using machine learning models based on grid search method. *Multimedia Tools and Applications*, 1–28.
16. Abdallah, S. E., Elmessery, W. M., Shams, M. Y., Al-Sattary, N. S. A., Abohany, A. A., & Thabet, M. (2023). Deep learning model based on ResNet-50 for beef quality classification. *Inf Sci Lett*, *12*(1), 289–297.
17. Shams, M. Y., Abd El-Hafeez, T., & Hassan, E. (2024). Acoustic data detection in large-scale emergency vehicle sirens and road noise dataset. *Expert Systems with Applications*, *249*, 123608. https://doi.org/10.1016/j.eswa.2024.123608
18. Shams, M. Y., Elzeki, O. M., Elaraby, M. E., & Hikal, N. A. (2020). Signature recognition based on support vector machine and deep convolutional neural networks for multi-region of interest. *J. Theor. Appl. Inf. Technol*, *98*(23), 3887–3897.
19. Hassan, E., Saber, A., & Elbedwehy, S. (2024). Knowledge distillation model for Acute Lymphoblastic Leukemia Detection: Exploring the impact of nesterov-accelerated adaptive moment estimation optimizer. *Biomedical Signal Processing and Control*, *94*, 106246. https://doi.org/10.1016/j.bspc.2024.106246
20. Sarhan, S., Nasr, A. A., & Shams, M. Y. (2020). Multipose Face Recognition-Based Combined Adaptive Deep Learning Vector Quantization. *Computational Intelligence and Neuroscience*, *2020*.
21. Hassan, E., Shams, M., Hikal, N. A., & Elmougy, S. (2021). Plant Seedlings Classification using Transfer Learning. In *2021 International Conference on Electronic Engineering (ICEEM)* (pp. 1–7). IEEE.
22. Hassan, E., Y. Shams, M., A. Hikal, N., & Elmougy, S. (2022). A Novel Convolutional Neural Network Model for Malaria Cell Images Classification. *Computers, Materials & Continua*, *72*(3), 5889–5907. https://doi.org/10.32604/cmc.2022.025629