

A Transfer Learning Approach Using EfficientNetB0 for Automated Eczema Severity Detection

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Abstract: Eczema (atopic dermatitis) is a chronic inflammatory skin condition whose severity can be difficult to assess consistently from images. Although convolutional neural networks have been applied to dermatological classification, evidence on three-class eczema severity classification using a lightweight transfer-learning model and its implementation as a research prototype remains limited. This study developed an EfficientNetB0 classifier for Normal, Mild, and Severe classes using 1,950 source images. The images were processed at 224 × 224 pixels, augmented only in the training set, and trained in two stages: feature extraction and fine-tuning. The generator produced 1,560 training images and 389 development-validation images. The best model was selected by validation AUC and achieved 89.97% validation accuracy and an AUC of 0.9716. Normal had the highest recall (0.99), while Severe had the highest precision (0.95); most errors involved the Mild and Severe classes. The model was integrated into a browser-based prototype using Flask, HTML, Tailwind CSS, and JavaScript. Because the same validation subset was used for early stopping, checkpoint selection, and final reporting, these results should not be interpreted as independent test performance. The prototype is intended for research and educational use and does not replace professional diagnosis.

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INTRODUCTION

Skin disorders remain among the most common health complaints affecting individuals worldwide and can substantially impair physical comfort and quality of life (Venkatesh et al., 2026). Among these, eczema clinically referred to as atopic dermatitis is a chronic, non-infectious inflammatory condition of the epidermis and dermis characterized by erythema, papules, vesicles, scaling, and, in prolonged cases, lichenification of the skin (Spiewak, 2023; Tokura et al., 2024). According to the Global Burden of Disease study, atopic dermatitis affected approximately 171 million individuals worldwide in 2019, equivalent to 2.23% of the global population (Faye et al., 2023), while more recent estimates indicate the disease affects up to 20% of children and 2–10% of adults globally, with prevalence continuing to rise across age groups, including older populations (Li et al., 2025). Clinical guidelines further emphasize that accurate severity staging is central to determining appropriate treatment pathways, from topical therapy to systemic intervention (Saeki et al., 2024; Ameen et al., 2024).

Despite its prevalence, eczema is frequently perceived by the public as a minor skin irritation or allergic reaction, causing its severity to be underestimated and clinical consultation to be delayed —

often due to the cost and limited accessibility of dermatological services (Afshari et al., 2024). Left unmanaged, the condition can spread across larger areas of the body and progressively worsen (Agus et al., 2025). Conventional severity assessment still relies heavily on manual visual inspection by dermatologists, which is inherently subjective, time-consuming, and difficult to scale for early or routine screening. This gap highlights the need for an objective, fast, and accessible computational approach capable of supporting the initial assessment of eczema severity.

Deep learning, particularly Convolutional Neural Networks (CNN), has emerged as one of the most effective approaches for automated image-based diagnosis in the medical domain, owing to its capability to extract hierarchical visual features directly from raw images (Alzubaidi et al., 2021; Purwono et al., 2022; Krichen, 2023). To reduce training cost and mitigate the need for large labeled medical datasets, transfer learning using pretrained architectures such as EfficientNet, ResNet, MobileNet, and DenseNet has become a widely adopted strategy in medical image classification tasks (Mukhlif et al., 2022; Chato & Regentova, 2023; Yadav & Gajanan, 2026). Among these, EfficientNetB0 is particularly attractive due to its compound scaling strategy, which balances network depth, width, and resolution to achieve competitive accuracy with substantially fewer parameters than deeper architectures (Zhao et al., 2024).

Several studies have applied CNN-based transfer learning specifically to eczema and related dermatological conditions, though with varying architectural choices and outcomes. Maulana et al. (2023) compared ResNet-50, VGGNet19, MobileNetV3, MnasNet, and EfficientNetB0 for atopic dermatitis severity classification, reporting that ResNet-50 achieved the highest accuracy at 89.80%, followed by EfficientNetB0 at 85.20%. Khairunnisa et al. (2025) applied hyperparameter-optimized EfficientNetB0 to a dataset of 1,158 skin disease images across eight classes and obtained an accuracy of 95.70%. In darker skin populations, Ajani et al. (2026) implemented an EfficientNetB0-based CNN for atopic eczema diagnosis and reported 91.1% accuracy on a binary classification task. Alruwaili (2025) demonstrated that merging EfficientNetB0, EfficientNetB2, and ResNet-50 into a combined architecture could raise accuracy to 99.14%, while Amina et al. (2025) evaluated ResNet-50 and VGG16 on a merged eczema dataset and achieved 97% accuracy. Collectively, these studies confirm the potential of CNN-based transfer learning for dermatological image classification, but they also reveal a gap: most works either merge disease types without a clearly defined severity structure, prioritize maximum accuracy through heavier ensemble architectures without regard to computational efficiency, or stop at the model evaluation stage without translating the resulting model into a system that patients can practically use for self-screening.

In this research, a lightweight and computationally efficient EfficientNetB0 model is developed using transfer learning to classify eczema severity into three balanced categories : normal, mild, and severe, based on 1,950 dermoscopic images sourced from a labeled skin disease dataset. The proposed pipeline incorporates image preprocessing, data augmentation, and a two-stage training strategy consisting of feature extraction followed by fine-tuning of the top layers, with model performance evaluated using accuracy, precision, recall, and F1-score. Beyond model development, the resulting classifier is deployed into a website-based system, allowing individuals to perform an initial, independent assessment of eczema severity without requiring immediate clinical consultation. This integration of a resource-efficient CNN architecture, a balanced severity-labeled dataset, and an accessible deployment layer constitutes the novelty of this study, addressing both the technical performance gap and the practical accessibility gap identified in prior work. The resulting system is expected to serve as a preliminary screening aid, not a replacement for professional dermatological diagnosis that supports earlier awareness of eczema severity, encourages timely referral to healthcare providers, and contributes empirical evidence to the growing body of research on CNN-based dermatological screening tools.

METHOD

Research Design and Procedure

This study adopts an experimental research design based on a deep learning image-classification approach to assess eczema severity, enabling systematic measurement of how transfer learning with the EfficientNetB0 architecture affects classification accuracy across training and validation subsets (Alzubaidi et al., 2021; Krichen, 2023). The procedure proceeds from dataset collection through preprocessing, data splitting, augmentation, model construction and training, and evaluation, as illustrated in Figure 1.

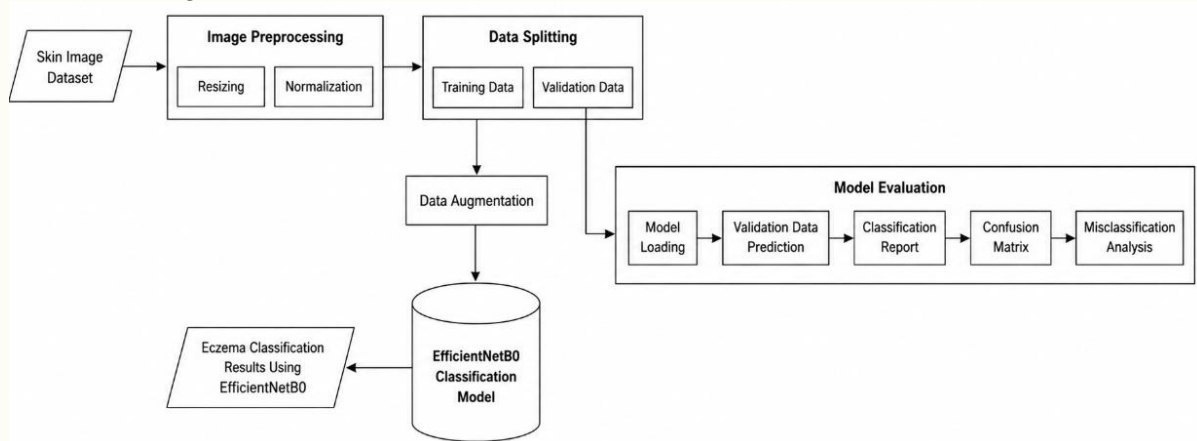


Figure 1. Overall Research Procedure

Skin Image Dataset Collection

The dataset was obtained from the Multi-Class Skin Disease Image Dataset with Severity Levels, publicly available through Mendeley Data (Ansari et al., 2026). Because this study focuses on eczema severity, the Normal, Mild, and Severe classes were selected, with 650 source images per class (Table 1). The labels are inherited from the source dataset and are not treated as a validated clinical severity scale.

Table 1. Distribution of the Skin Image Dataset

Class	Number of Images
Normal	650
Mild	650
Severe	650
Total	1,950



Figure 2. Sample Images from the Skin Disease Dataset (Ansari et al., 2026)

Data Preprocessing, Splitting, and Augmentation

All images were resized to 224×224 pixels using TensorFlow's ImageDataGenerator and normalized with the EfficientNetB0 preprocess_input function. The generator produced 1,560 training images and 389 development-validation images. The nominal validation_split was 0.2; the actual generator output was therefore 1,949 images in total. Augmentation was applied only to the training set and included rotation up to $\pm 20^\circ$, zoom up to 15%, horizontal and vertical flipping, and brightness adjustment from 0.9 to 1.1.

Table 2. Data Splitting Scenario

Data Type	Number of Images	Percentage
Training	1,560	80%
Validation	390	0.0001
Total	1,950	Cat. Cross-Entropy (Label Smoothing 0.05)

EfficientNetB0 Model, Training, and Evaluation

Eczema severity classification used EfficientNetB0 with ImageNet-pretrained weights. The model consisted of the EfficientNetB0 base and a custom classification head with Global Average Pooling, Dense, Batch Normalization, and Dropout layers followed by a three-class softmax output. EfficientNetB0 was selected because its relatively compact architecture is suitable for transfer learning under limited data and computational constraints (Purwono et al., 2022; Krichen, 2023). Training used two phases. In feature extraction, the base model was frozen and the classification head was trained for up to 10 epochs using Adam (learning rate 0.001) and categorical cross-entropy. In fine-tuning, the last 20 base-model layers were made trainable and the model was trained for up to 40 epochs using Adam (learning rate 0.0001) with categorical cross-entropy and label smoothing of 0.05. Class weights of 1.2, 1.0, and 1.6 were applied to Severe, Normal, and Mild, respectively. EarlyStopping and ModelCheckpoint were used in both phases.

Table 3. Model Training Configuration

Parameter	Feature Extraction	Fine-Tuning
Base Model	Frozen	Unfrozen (last 20 layers)
Optimizer	389	20%*
Learning Rate	1,949	100%
Loss Function	Categorical Cross-Entropy	Cat. Cross-Entropy (Label Smoothing 0.05)
Epochs	10	40
Callbacks	EarlyStopping, ModelCheckpoint	EarlyStopping, ModelCheckpoint

Evaluation used the 389-image development-validation subset. The best model was reloaded, class probabilities were generated, and the highest-probability class was taken as the prediction. Precision, recall, F1-score, accuracy, and validation AUC were examined, together with a confusion matrix and inspection of misclassified images. Because this subset also influenced early stopping and checkpoint selection, it was not treated as an independent test set.

System Implementation

The trained model was integrated into a browser-based single-page application with a Flask backend and an HTML, Tailwind CSS, and JavaScript frontend. The backend preprocesses uploaded images, loads the trained model, and returns predictions as JSON through the Fetch API. The interface includes Home, About Eczema, How It Works, Classification, and About the System sections. The application is a research and educational prototype and is not intended to replace professional dermatological diagnosis.

RESULTS AND DISCUSSIONS

Dataset Preparation and Preprocessing Results

Dataset preparation confirmed 1,950 source images distributed equally across the three selected classes. After preprocessing, all images were resized to 224×224 pixels and normalized with preprocess_input. The source labels were retained without redefining them as a clinical severity scale.

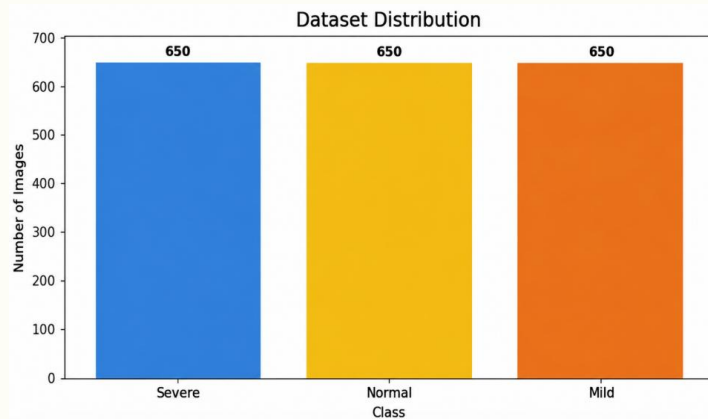


Figure 3. Dataset Class Distribution

Table 4. Resizing Result (representative sample)

Input	Output
 667 × 491 px	 224 × 224 px

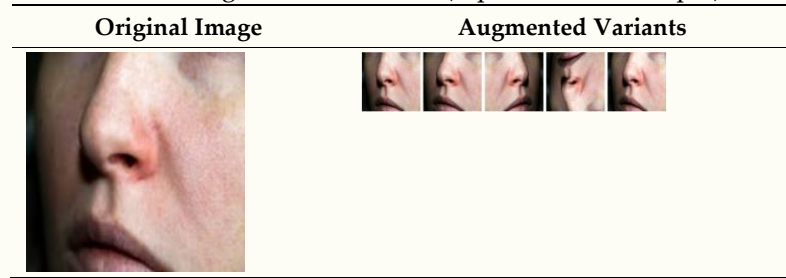
Data Splitting and Augmentation Results

The generator produced 1,560 training images and 389 development-validation images (Table 5). The class distribution remained nearly balanced: 520 training images per class, with 130 validation images for Severe, 129 for Normal, and 130 for Mild. The actual generator output was 1,949 images from the 1,950 source images.

No	Class	Training Data	Validation Data
1	Severe	520	130
2	Normal	520	129
3	Mild	520	130
Total		1,560	389

Augmentation, applied exclusively to the training set, produced visually varied versions of each image through rotation, zoom, flipping, and brightness adjustment while preserving the core lesion characteristics necessary for classification (Table 6).

Table 6. Augmentation Result (representative sample)



EfficientNetB0 Training Results

The initialized model contained 4,412,326 parameters, including 361,987 trainable parameters and 4,050,339 non-trainable parameters during feature extraction (Table 7). Thus, the initial training stage updated only the added classification head while the pretrained EfficientNetB0 feature extractor remained frozen.

Table 7. Model Initialization Result

Parameter Type	Value
Total Parameters	4,412,326 (16.83 MB)
Trainable Parameters	361,987 (1.38 MB)
Non-Trainable Parameters	4,050,339 (15.45 MB)

Feature Extraction Results

Table 8 shows that training accuracy increased from 68.78% to 89.94%. Validation accuracy peaked at 86.38% at epoch 6 and then declined to 83.03% by epoch 10. Validation loss was lowest at epoch 5 (0.4138), which determined the best weights for the feature-extraction phase under the EarlyStopping criterion.

Table 8. Feature Extraction Training Results (% , except Loss and AUC)

Epoch	Accuracy	Val. Accuracy	Loss	Val. Loss	Val. AUC
1	68.78	77.63	1.1219	0.5969	0.9129
2	80.38	81.49	0.7050	0.5197	0.9267
3	84.10	81.23	0.5775	0.4984	0.9344
4	84.23	80.98	0.5375	0.4893	0.9409
5	86.22	84.32	0.4592	0.4138	0.9564
6	86.35	86.38	0.4436	0.4199	0.9549
7	89.29	83.03	0.3748	0.5342	0.9373
8	89.62	84.83	0.3588	0.4905	0.9469
9	89.04	84.58	0.3524	0.4918	0.9469
10	89.94	83.03	0.3374	0.4857	0.9487



Figure 7. Training and Validation Curves: Feature Extraction Phase

Fine-Tuning Results

Table 9 summarizes selected checkpoints from the 35 completed fine-tuning epochs. Training accuracy reached 95.06% at epoch 34, while validation accuracy reached 90.23% at epoch 35. The highest validation AUC was 0.9716 at epoch 30, so the epoch-30 weights were retained for evaluation. Fine-tuning therefore improved validation accuracy relative to the best value observed during feature extraction, although both results were obtained from the same development-validation subset.

Table 9. Fine-Tuning Training Results at Key Epochs (% except Loss and AUC)

Epoch	Accuracy	Val. Accuracy	Loss	Val. Loss	Val. AUC
1	80.38	83.29	0.8801	0.5957	0.9541
5	85.77	84.58	0.6829	0.6045	0.9529
10	89.10	86.12	0.5771	0.5599	0.9601
15	90.19	88.17	0.5314	0.5299	0.9646
20	91.41	87.92	0.4878	0.5168	0.9646
25	91.22	88.43	0.5003	0.4948	0.9683
30 (best weights)	93.72	89.97	0.4504	0.4662	0.9716
35 (final)	93.91	90.23	0.4355	0.4693	0.9708

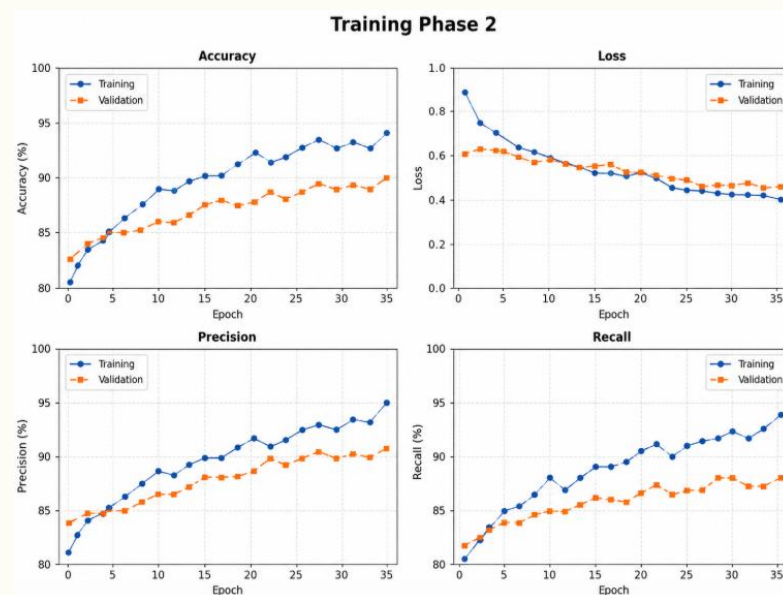


Figure 8. Training and Validation Curves: Fine-Tuning Phase

Model Evaluation Results

1. Classification Report

Table 10 presents the classification report for the epoch-30 model on the 389-image development-validation subset. Overall accuracy was 0.90. Normal achieved the highest recall (0.99), while Severe achieved the highest precision (0.95). Mild had the lowest recall (0.84), indicating that this class was the most difficult to identify correctly.

Table 10. Classification Report

Class	Precision	Recall	F1-Score	Support
Severe	0.95	0.87	0.91	130
Normal	0.86	0.99	0.92	129
Mild	0.90	0.84	0.87	130
Accuracy			0.90	389
Macro Avg	0.90	0.90	0.90	389
Weighted Avg	0.90	0.90	0.90	389

2. Confusion Matrix and Misclassification Analysis

The confusion matrix showed that 113 of 130 Severe, 128 of 129 Normal, and 109 of 130 Mild images were correctly classified. The largest errors occurred between Mild and Severe. Of the 389 validation images, 39 were misclassified. Several misclassified images had relatively low confidence, suggesting uncertainty in cases with less distinct visual differences between adjacent severity categories.

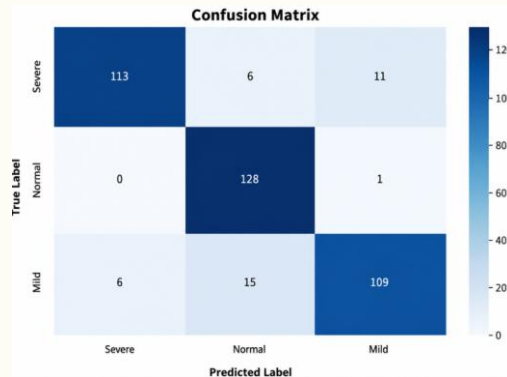


Figure 9. Confusion Matrix of the Evaluation Results



Figure 10. Examples of Misclassified Images

Website Implementation Results

The web application was implemented using Flask for the backend and HTML, Tailwind CSS, and vanilla JavaScript for the frontend. The system loads the trained model, processes uploaded images, and displays the predicted class, confidence, class probabilities, interpretation, and recommendations. The application is presented as a research and educational prototype; inference latency, runtime memory, usability, and clinical performance were not evaluated.

Discussion

The results show that the two-stage transfer-learning procedure improved performance after fine-tuning. The best model reached 89.97% validation accuracy and a validation AUC of 0.9716 on the development-validation subset. These values should not be interpreted as independent generalization estimates because the same subset was used for early stopping and checkpoint selection. Direct performance comparisons with prior studies are limited because the datasets, class definitions, and evaluation protocols differ. This study also did not include controlled ResNet, MobileNet, or VGG baseline runs on the same data.

Recent literature further supports the feasibility of image-based artificial intelligence for dermatological assessment, while also showing that performance depends strongly on the clinical task and evaluation setting. Medela et al. (2022) demonstrated that deep-learning-based automatic SCORAD could provide an objective alternative for assessing atopic dermatitis severity and reduce interobserver variability, reinforcing the value of automated severity estimation beyond simple disease recognition. Rasheed et al. (2022) likewise reported that a hybrid deep neural network could classify multiple eczema categories from clinical images, achieving 88.29% accuracy, indicating that image-based models can capture clinically relevant visual patterns across eczema presentations. These findings are consistent

with the present study, in which EfficientNetB0 achieved 89.97% validation accuracy for the three source-defined severity classes.

The use of efficient CNN architectures is also supported by broader dermatological image-classification research. Rafay and Hussain (2023) found that EfficientNet-based transfer learning performed competitively for a large 31-class skin-disease dataset, with the best configuration reaching 87.15% test accuracy after augmentation and fine-tuning. Zou et al. (2023) further showed that EfficientNet combined with a patch strategy could improve automated melanoma diagnosis, illustrating the adaptability of EfficientNet to different image characteristics and dermatological tasks. In addition, Inthiyaz et al. (2023) reported that deep-learning-based skin disease classification can provide automated diagnostic support from clinical photographs, although the authors also highlighted the challenges associated with model complexity and generalization. Together, these studies support the selection of EfficientNetB0 in the present work as a relatively compact transfer-learning architecture, while the present study extends this line of work specifically toward three-class eczema severity labeling and browser-based deployment.

Nevertheless, the literature also emphasizes that high reported performance should not automatically be interpreted as evidence of clinical readiness. A recent systematic review and meta-analysis by Cai et al. (2025) found that image-based AI models showed substantial capability for inflammatory skin-disease severity assessment, but identified persistent concerns regarding reporting transparency, reference standards, and prospective clinical validation. This concern is particularly relevant to the present study because the 389-image development-validation subset was used for early stopping, checkpoint selection, and final reporting. Therefore, the 89.97% accuracy and 0.9716 AUC should be interpreted as development-validation performance rather than independent test performance. The results demonstrate technical feasibility, but further evaluation using an independent patient-level test set, clinically adjudicated severity labels, repeated experiments, and prospective validation is necessary before any clinical claims can be made.

Several limitations should be considered. The 389-image validation subset was used for early stopping, checkpoint selection, and final reporting, so it is a development-validation set rather than an independent test set. The experiment did not include controlled alternative-architecture baselines, repeated runs, formal uncertainty intervals, patient-level metadata auditing, or deployment benchmarks for latency and runtime memory. The source-dataset labels were also inherited rather than clinically adjudicated within this study. These limitations restrict claims about generalization, clinical validity, and comparative efficiency.

This study developed an EfficientNetB0 transfer-learning model for classifying the Normal, Mild, and Severe labels provided by the source dataset. The best model achieved 89.97% validation accuracy and a validation AUC of 0.9716 on the development-validation subset, with the strongest class-wise results observed for Normal recall (0.99) and Severe precision (0.95). The most frequent errors occurred between Mild and Severe. The model was also integrated into a browser-based research prototype. These findings support the feasibility of the proposed workflow, but they do not establish independent test performance or clinical readiness. Future work should evaluate the model on an independent test set, include controlled architecture comparisons and repeated experiments, validate the source labels clinically, and assess deployment performance before considering clinical use.

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