Deep Learning Based Detection and Classification of Skin Diseases

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Abstract

Skin diseases, ranging from acne to deadly melanoma, pose a major global health issue. Accurate, timely diagnosis is essential for effective treatment, but traditional methods are time-consuming and prone to human error. Advances in artificial intelligence, especially deep learning, now enable faster, more accurate dermatological diagnoses. This study explores deep learning techniques for classifying skin diseases using Convolutional Neural Networks (CNNs). Eight pre-trained models—including EfficientNet-B0, NASNet-Mobile, InceptionV3, ResNet variants, ShuffleNet, GoogleNet, and Inception_ResNet-v2—were evaluated using a Kaggle dataset. The focus was on classifying four key conditions (Acne, Rosacea, Eczema, Melanoma/Nevi) and identifying Urticaria. Models were assessed on accuracy, precision, recall, and F1 score. EfficientNet-B0 and ResNet-101 outperformed others, especially in detecting Melanoma/Nevi and Urticaria. While NASNet-Mobile showed lower accuracy, its lightweight design suits mobile use. Challenges remain, particularly in improving recall. The findings affirm deep learning's value in dermatology and lay groundwork for AI-driven diagnostic systems. Future work will aim to boost generalization, mobile performance, and recall accuracy.

Keywords: Skin Disease, Detection, Deep Learning, Convolutional Neural Networks, AI in Dermatology, Machine Learning, Automated Diagnosis.

Introduction

The skin is the most effective defense mechanism for vital organs in the human body. It serves as a barrier to prevent injury to the interior organs. However, this vital organ is susceptible to harmful diseases caused by fungi, viruses, or even environmental factors such as dust (Inthiyaz et al., 2023). Skin diseases form a major global health problem because they cover the spectrum of acne as a minor ailment and to melanoma as a lethal condition. According to the World Health Organization (WHO), millions of people worldwide suffer from skin diseases (Li et al., 2021). Owing to the identifiable patterns of skin diseases, doctors are focusing on

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diagnostic models on these conditions specifically because these models for can be automated and standardized. Dermatology research has progressed, but early disease identification and precise condition categorization remain challenging because skin disorders have various complexities and show modifications between diagnostic sessions (Ahammed et al., 2022). The present diagnostic processes depend strongly on dermatologists making clinical judgments while enduring extended diagnosis times which also have the potential for human mistakes. According to Goceri (2021), rapid development in AI and ML, specifically in deep learning, have enabled automated skin disease detection systems to become prominent diagnostic tools. These technological systems provide quick, precise, and expandable solutions to dermatological concerns, which could lead to their adoption in mobile and clinical spaces.

Convolutional Neural Networks (CNNs) received widespread interest among deep learning techniques because they demonstrate powerful performance during image classification operations (Allugunti, 2022). The ability of CNNs to discover image-based hierarchical characteristics makes them ideal for dermatological examinations because patterns in skin lesions form a vital component of diagnosis. The models demonstrate automatic capability for skin condition detection such as melanoma, eczema, psoriasis, and acne through accuracy, which rivals the performance of human dermatologists (Li et al., 2021; Abbas et al., 2022). Deep learning in diagnostics faces challenges such as the need for large, annotated datasets, generalizability across diverse populations, and real-time application (Wu et al., 2020; Goceri, 2021). Ethical and privacy concerns must also be addressed when using patient data for model training. This study evaluated the effectiveness of pre-trained CNNs in identifying and classifying various skin diseases (UdriŞtoiu et al., 2020). The findings support the development of automated AI-based dermatology systems aimed at improving patient outcomes and highlight key areas for future research.

Literature Review

Millions of individuals worldwide experience a significant public health burden due to skin diseases. Identifying skin conditions early and making precise diagnoses enable correct treatment methods, and improves healthcare results (Pacheco et al., 2019). The field of skin disease detection and classification has undergone experienced a transformation through deep learning, which has operated as a subset of artificial intelligence in recent years (Bajwa et al., 2020). Deep learning-based algorithms have proven highly effective in automating skin disease diagnosis, providing a promising solution to dermatologist shortages and medical resource limitations (Pacheco et al., 2019). These algorithms process unprocessed data through image analysis before learning discriminatory features that help identify hidden patterns, leading to an accurate, and reproducible diagnosis.

Several studies have demonstrated that deep learning achieves accurate human-level diagnosis outcomes for various skin disease categories. Such advancements bring substantial benefits to dermatology because they enable massive screenings while helping doctors make better professional choices (Bajwa et al., 2020). A study suggested the development of an adaptive federated machine learning-based skin disease model that moves toward building an intelligent dermoscopy device for dermatologists. The research community has evaluated the benefits and drawbacks of deep learning for skin disease classification because this developing field aims to resolve the problem of insufficient medical personnel. (Zhang et al., 2021). ALEnezi et al. (2019) research group created advanced tools that merged image processing methods with machine learning algorithms for skin disease recognition. This research applies feature extraction methods to skin images, which helps to establish different disease classifications. The achievement of early disease detection classification depended on use of Support Vector Machines (SVM) and K-nearest neighbors (KNN) algorithms.

Malliga et al. (2020) examined how deep learning algorithms identify and categorize skin diseases. This study analyzes CNNs for image classification because these networks exhibit high effectiveness in this domain. The study examines normalization and augmentation procedures because they improve model accuracy when processing large datasets. A study confirmed that CNNs deliver superior performance compared to conventional machine learning methods in detecting and diagnosing conditions such as psoriasis and melanoma. Elngar et al. (2021) described an intelligent prediction system for skin diseases using machine learning. This study develops a predictive integration of ensemble models and decision trees for superior performance. The system focuses on developing feature selection and optimization methods, which are key components for improving system performance. Mohammed and Al-Tuwaijari (2021) reviewed machine learning methods for skin disease classification, comparing algorithms like SVM, Random Forest, and Deep Learning. They noted key challenges, including class imbalance, the need for large, labeled datasets, and efficient feature extraction. Son et al. (2021) focused on AI-based localization and classification of erythematous skin lesions using U-Net architectures for segmentation. They found AI methods outperform traditional ones, especially in complex or poorly visualized cases.

Srinivasu et al. (2021) proposed a hybrid MobileNetV2–LSTM model for skin disease detection in temporal data, achieving high accuracy with low computational cost—suitable for tracking skin conditions over time. Pugazhenthi et al. (2019) highlighted the effectiveness of CNN-based models on real-world, variable-quality images. They emphasized fine-tuning pre-trained models over training from scratch. Okuboyejo et al. (2013) used KNN and SVM with color and texture features for image-based skin disease classification, supporting the viability of automated diagnosis.

Methodology

This study investigated the application of deep transfer learning techniques for skin disease detection and classification. The method includes various sequential steps, as presented in the process flow diagram shown in Figure 1.

Figure 1: Process Flow Diagram.

Collection of Dataset

Kaggle, a leading repository for machine learning datasets, is the platform from which this study received its dataset. Kaggle offers researchers access to high-quality data collection, including medical disease detection and classification materials. The open-access DermNet dataset, which provides skin disease labels, contained 23,000 clinical images. The dataset supplied all data assets, such as medical images, clinical documentation, and necessary materials for model testing and training processes.

Dataset Preprocessing

The DermNet dataset contained class imbalance, which was addressed through augmentation methods including horizontal/vertical flipping, ±15° rotation, and zoom transformations. Images were resized to 224×224 pixels, normalized to the [0,1] range, and shuffled each epoch.

Diseases Selection

Acne, Rosacea, Eczema, Melanoma Skin Cancer, Nevi, Moles, and Urticaria (Hives) were examined in this study. The research focused on these four diseases through two significant considerations: their clinical significance alongside matching database resources available on Kaggle and the present-day medical investigation value. This study included different skin disease types to assess the cross-application capabilities of deep-learning models for various skin conditions. The diseases selected for detection and classification include these four conditions.

Acne and Rosacea

Acne, common in youth and young adults, results from clogged hair follicles and is often triggered by hormonal changes and bacteria, causing pimples, blackheads, and cysts. Rosacea is a chronic condition marked by facial flushing and visible blood vessels, with triggers including stress, environmental factors, and certain foods (Son et al., 2021).

Eczema

Eczema, or atopic dermatitis, is a chronic skin inflammation causing redness, swelling, and itching. It's often linked to genetic allergies and worsened by stress, irritants, and environmental factors (Mohammed & Al-Tuwaijari, 2021).

Melanoma Skin Cancer, Moles, and Nevi

Melanoma is an aggressive skin cancer arising from pigment cells but is highly treatable if caught early. Nevi (moles) are usually benign but can become malignant with changes in size, color, or shape. Early detection is key to prevention (Malliga et al., 2020).

Urticaria (Hives)

Urticaria, or hives, is a red, itchy skin rash usually triggered by allergens, infections, drugs, or stress. It can be acute or chronic and, while not typically dangerous, may signal an underlying condition (Elngar et al., 2021).

Figure 2: Acne and Rosacea

Figure 3: Eczema

Figure 4: Melanoma

Figure 5: Urticaria Hives

Applying Different Deep Transfer Learning Models (Pre-Trained CNN)

After selecting the target diseases, several pre-trained deep transfer learning models were applied for classification. These CNN-based models—EfficientNet-B0, NASNet-Mobile, InceptionV3, ResNet-18/50/101, ShuffleNet, GoogleNet, and Inception_ResNet-v2—were chosen for their proven image classification performance and unique architectural strengths. EfficientNet-B0 and NASNet-Mobile stood out for mobile efficiency, while deeper models like InceptionV3 and ResNets excel in handling complex tasks. ShuffleNet was noted for its lightweight design, ideal for resource-constrained environments. All models were fine-tuned on disease-specific datasets to boost classification accuracy.

Selecting Optimal Models

Performance testing assesses the selected four diseases for each created model. Each model is measured using accuracy, precision, recall, and F1 score as evaluation metrics. Further evaluation and tuning focus on the most successful models based on these results. The process selects top-performing models for the next stage.

Update Parameters & Again Applying Different Deep Transfer Learning Models (Pre-Trained CNN)

The model parameters and hyperparameters are re-tuned based on the initial test results. The models are then re-run on the datasets with the updated parameters, and the loop is repeated to enhance performance. This iterative process aims to optimize and refine the models.

Finding Performance Indicators for Every Trained Model

Every trained model is thoroughly examined, and key performance indicators (KPIs) are identified to evaluate its effectiveness. These include receiver operating characteristics (ROC), precision, recall, confusion matrices, and other statistical measures. Identifying these metrics allows for a clear assessment of each model's efficiency across the different diseases.

Deciding Best Models for Every Disease

The performance criteria and the most suitable models for each disease are identified. Model selection is based not only on classification accuracy but also on computational efficiency and processing speed, ensuring practical applicability alongside diagnostic performance.

Results and Discussions

This study used several pre-trained deep-learning models to detect and classify skin diseases based on data collected from Kaggle. The models used for testing were EfficientNet-B0, NASNet-Mobile, InceptionV3, ResNet-50, ResNet-101, ShuffleNet, ResNet-18, and GoogleNet. The diseases used in this study were Acne and Rosacea, Eczema, Melanoma/Nevi and Moles, and Urticaria (Hives). The models were fine-tuned for each disease, and several performance metrics were computed, including accuracy, precision, recall, and F1 score. Table 1 shows the results of the models used in this study.

Table 1: Comparative results of different model for four diseases including Accuracy, Precision, Recall and F1-Score.

Model	Disease	Accuracy	Precision	Recall	F1 Score
EfficientNet-b0	Acne and Rosacea	0.9051	0.8615	0.9032	0.8819
	Eczema	0.9114	0.8529	0.9355	0.8923
	Melanoma/Nevi & Moles	0.9241	0.7895	0.6522	0.7143
	Urticaria Hives	0.9684	1.0000	0.5455	0.7059
NASNet-Mobile	Acne and Rosacea	0.8797	0.8308	0.8710	0.8504
	Eczema	0.8481	0.8393	0.7581	0.7966
	Melanoma/Nevi & Moles	0.9114	0.6957	0.6957	0.6957
	Urticaria Hives	0.9304	0.5000	0.6364	0.5600
InceptionV3	Acne and Rosacea	0.8987	0.8382	0.9194	0.8769
	Eczema	0.8924	0.8261	0.9194	0.8702
	Melanoma/Nevi & Moles	0.9304	1.0000	0.5217	0.6857
	Urticaria Hives	0.9620	0.7778	0.6364	0.7000
ResNet-50	Acne and Rosacea	0.8101	0.7286	0.8226	0.7727
	Eczema	0.8291	0.7692	0.8065	0.7874
	Melanoma/Nevi & Moles	0.9051	0.7857	0.4783	0.5946
	Urticaria Hives	0.9494	0.6667	0.5455	0.6000
ResNet-101	Acne and Rosacea	0.9177	0.8958	0.9516	0.9008
	Eczema	0.8861	0.8854	0.8871	0.8594
	Melanoma/Nevi & Moles	0.9114	0.9778	0.5217	0.6316
	Urticaria Hives	0.9557	0.9864	0.5455	0.6316
Shuffle Net	Acne and Rosacea	0.8797	0.8413	0.8548	0.8480
	Eczema	0.8671	0.8475	0.8065	0.8264
	Melanoma/Nevi & Moles	0.8924	0.6154	0.6957	0.6531
	Urticaria Hives	0.9684	0.8000	0.7273	0.7619
ResNet-18	Acne and Rosacea	0.8924	0.6154	0.6957	0.6531
	Eczema	0.9684	0.8000	0.7273	0.7619
	Melanoma/Nevi & Moles	0.8291	0.7160	0.9355	0.8112
	Urticaria Hives	0.8291	0.9070	0.629	0.7429
Google Net	Acne and Rosacea	0.8608	0.7564	0.9516	0.8429
	Eczema	0.8544	0.8197	0.8065	0.813
	Melanoma/Nevi & Moles	0.9304	1.0000	0.5217	0.6857
	Urticaria Hives	0.9494	0.7143	0.4545	0.5556
Inception_ResNet-v2	Acne and Rosacea	0.8861	0.8793	0.8226	0.8500
	Eczema	0.8924	0.8169	0.9355	0.8722
	Melanoma/Nevi & Moles	0.8924	0.6500	0.5652	0.6047
	Urticaria Hives	0.9494	0.6667	0.5455	0.6000

Among the models, EfficientNet-B0 performed best, achieving an accuracy of 92.41% in distinguishing Melanoma/Nevi and Moles from Urticaria (Hives) with a staggering accuracy of 96.84%. The precision of Urticaria (Hives) was perfect at 1, even though the recall was very poor at 54.55%, indicating that though the model was very precise in identifying the disease when it was present, it did not catch all relevant cases. ResNet-101 achieved strong performances with an accuracy of 91.14% in distinguishing Melanoma/Nevi and Moles and 95.57% in distinguishing Urticaria (Hives). The precision of ResNet-101 was very good for most diseases, especially for Acne and Rosacea (0.8958) and Melanoma/Nevi and Moles (0.9778). However, its recall was lower, especially for Urticaria (Hives), where the recall was 54.55% only.

NASNet-Mobile demonstrated the lowest performance in disease detection, specifically with Melanoma/Nevi and Moles (91.14%) and Urticaria (Hives) (93.04%). Yet, its precision levels were reasonable across the other diseases, particularly Acne and Rosacea (0.8308). This model's lower accuracy does not hinder its influence for mobile applications because of its efficient speed and performance. InceptionV3 and EfficientNet-B0 both achieved 92.04% accuracy for Melanoma/Nevi and Moles, and 96.20% for Urticaria. However, InceptionV3 showed lower recall for Melanoma (52.17%) and Urticaria (63.64%). ShuffleNet and ResNet-18 performed adequately for Melanoma/Nevi and Moles (86.84% and 82.91% accuracy) but underperformed in identifying Acne, Rosacea, and Urticaria.

To validate performance, our proposed models were compared against benchmark classifiers including SVM, KNN, and Random Forest trained on the same dataset. While traditional models achieved accuracies between 65–78%, the CNN-based architectures exceeded 90% accuracy across most classes. Improvements were most notable in recall, where deep learning models reduced false negatives significantly, a critical factor in medical applications. Deep learning models, especially pre-trained CNNs, are highly effective for skin disease classification. EfficientNet-B0 and ResNet-101 showed the best results in detecting Melanoma/Nevi, Urticaria, and Moles, thanks to their deep architectures. EfficientNet-B0 combines strong performance with low computational cost, making it ideal for mobile and real-time use, while ResNet-101 enhances diagnostic precision by reducing false positives.

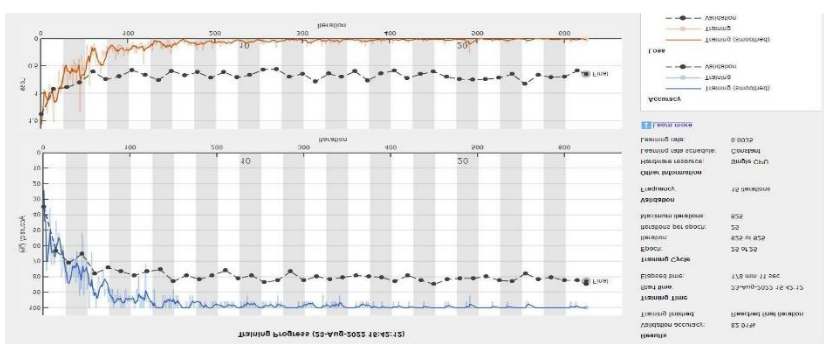

Figure 6: Training Graph of Efficient Net-b0

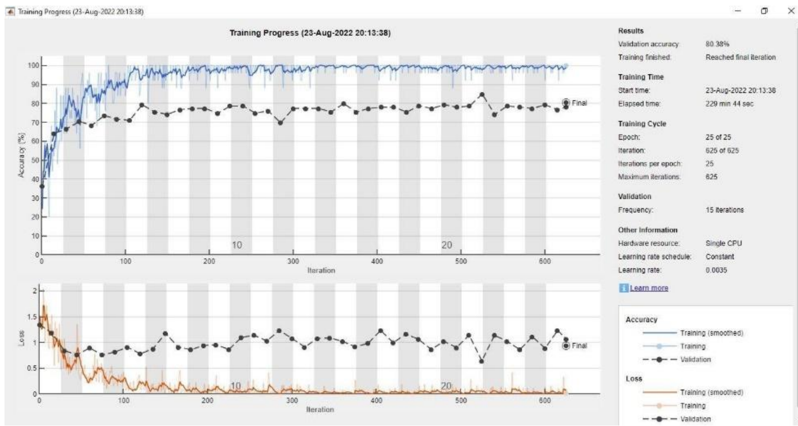

Figure 7: Training Graph of NASNet-Mobile

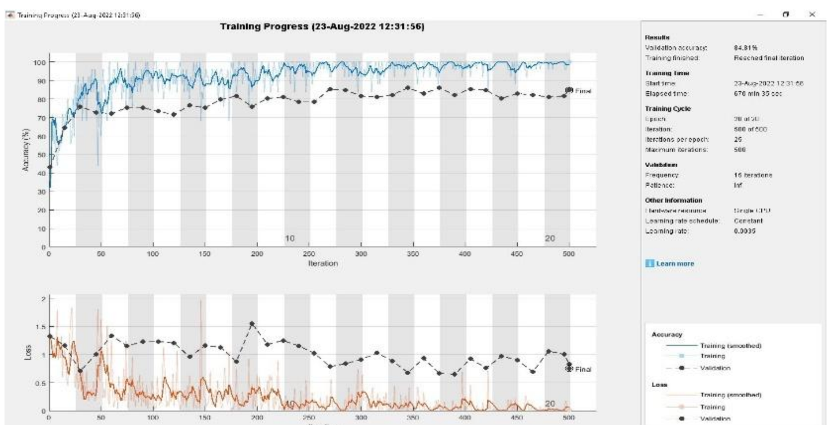

Figure 8: Training Graph of InceptionV3

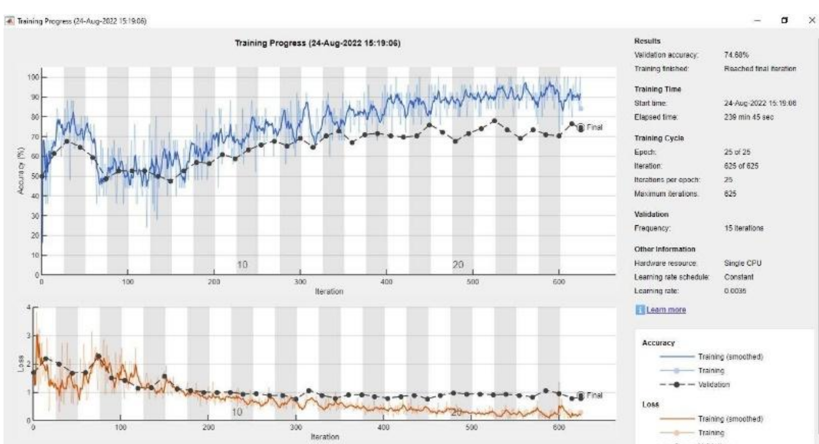

Figure 9: Training Graph of ResNet-50

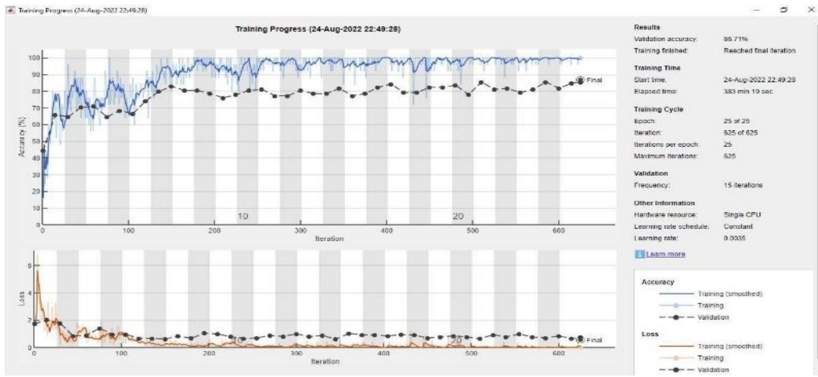

Figure 10: Training Graph of ResNet-101

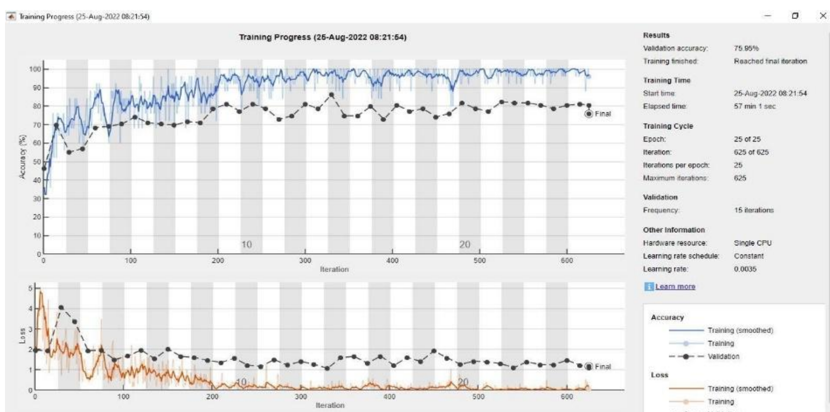

Figure 11: Training Graph of Shuffle Net

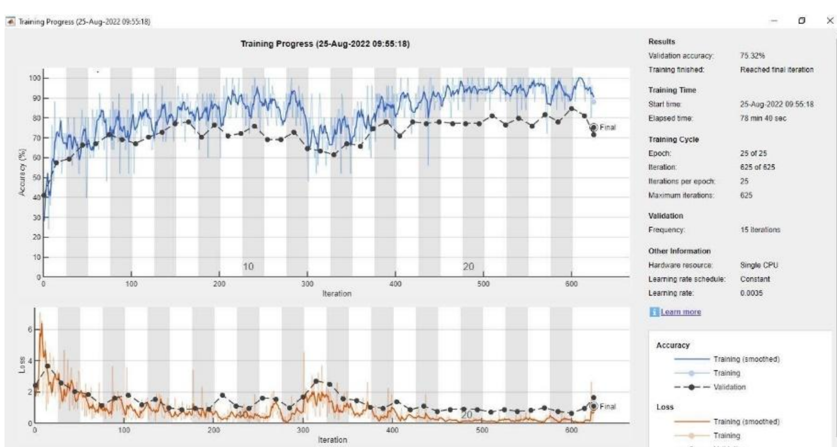

Figure 12: Training Graph of ResNet-18

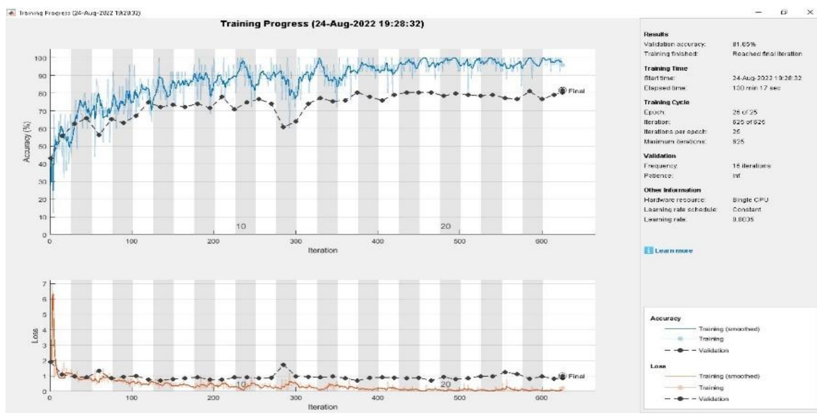

Figure 13: Training Graph of GoogleNet

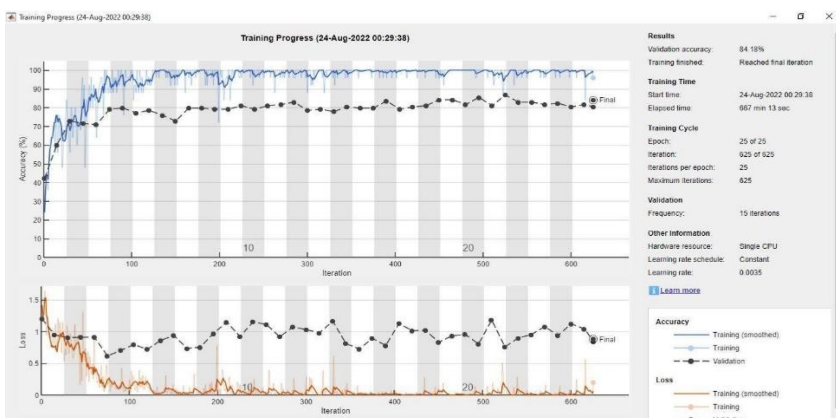

Figure 13: Training Graph of Inception-ResNet-V2

Despite its reduced accuracy through efficient processing, NASNet-Mobile presents the potential for real-time mobile health applications. ShuffleNet and ResNet-18 operate at high speed, offering quick feedback capabilities despite having moderate accuracy levels, thus making them appropriate for real-time use with limited resources. Models performing uniquely among diseases require investigators to maintain a balance between accuracy and precision in addition to recall for diagnosing Urticaria (Hives) precisely because these models achieve high accuracy but face difficulties in recall. The research shows that deep learning-based skin disease classifiers offer multiple efficiency-diagnostics reliability trade-offs during diagnostic classification tasks.

A key observation is the trade-off between precision and recall. For instance, EfficientNet-B0 achieved 96.84% accuracy and perfect precision in detecting Urticaria but had a low recall of 54.55%, indicating missed cases. Clinically, this underscores the need to prioritize recall to reduce under-diagnosis. Deeper models like ResNet-101 showed better recall than lightweight models, making them more suitable for clinical use, while mobile-optimized models like NASNet-Mobile are better suited for initial screening. These findings support the work of Bajwa et al. (2020), Malliga et al. (2020), and recent transformer-based studies (Chen et al., 2023), reinforcing the strengths of deep CNNs and the persistent challenges of class imbalance and recall.

Conclusion and Future Work

Deep learning models, especially pre-trained CNNs, are powerful tools for skin disease diagnosis. Future research will incorporate fuzzy logic to rank model performance, address low recall in less prevalent diseases, and improve generalization to new datasets. Efforts will also focus on optimizing models for mobile-based, real-time applications requiring high accuracy and efficiency. External validation using datasets like ISIC-2020 and PH² will ensure robustness, while 5-fold cross-validation will support consistency. Focal loss functions will be explored to improve minority class detection, and reinforcement learning may be applied to develop adaptive diagnostic pipelines for real-time clinical support.

Conflicts of Interest: The authors declare no conflicts of interest.

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