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OPTIMIZING DEEP LEARNING MODELS FOR LARGE-SCALE, MULTI-CLASS SKIN DISEASE CLASSIFICATION IN CLINICAL DERMATOLOGY

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Abstract

Based on deep learning skin disease classification has progress a key tool To improve dermatological diagnosis, especially on a large scale, multi- class scenarios. By using a balanced dataset more than 260, 000 dermatoscopic images from 35 different skin disease classes which was taken from Kaggle, This study investigates the capabilities of top convolutional neural network(CNN) architectures. Appreciate the model InceptionResNetV2, sectionv3, ResNet50, Efficient NetB4, and MobileNetV2 I am evaluated the study, side by side ensemble strategies Favor EfficientNetB3 in conjunction with ResNet50 and MobileNetV2. Keeping exercise hours manageable, ResNet50 prepared the best validation accuracy K 97.91% Watch carefully among them InceptionResNetV2 and InceptionV3 on 93.94% And 93.02%, In addition, respectively ensemble models demonstrated a high capacity To generalize. These findings Illustrate how vital it is to distribute AI Finding a balance between accuracy, scalability and computational efficiency AI models I clinical dermatology, Especially in a resource- constrained environment. By encouraging early and effectively detection of skin disorders, This study demonstrates the authority of AI diagnostic systems.

Keywords: Skin Disease, deep learning, CNN, Resnet 50, Classification, Dermatology, ensemble learning

1. Introduction

1.1 Background and Motivation

The skin, which is the biggest organ in the human body, As it serves a crucial defense against the environment dangers Even while regulating body temperature, Facilitation sensory perception, And invigorating the immune system. Millions people worldwide Everyone suffers

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from skin diseases year, to establish them one Most of all common health problems. Responsible for dermatological disorders 4.02% K all years Lived with disability(YLDs) I India alone. These diseases vary from common, mild issues Esteem eczema and acne To do more serious conditions Appreciate psoriasis and melanoma, The latter was more responsible 55, 000 deaths worldwide I 2020. Although methods such as patch test, potassium hydroxide(KOH) testing, Dermatoscopy and biopsy have improved dermatological diagnostics, They are usually invasive, duration consuming and addictive expert interpretation. Kim and me rural areas, Where there is limited access qualified dermatologists, It offers a serious problem.

New developments I deep learning And other areas K artificial intelligence(AI) is displayed great promise In conclusion this gap. Through image analysis, Synchronous nervous system Network(CNNs), including popular architectures Esteem ResNet, What is prepared? impressive results I the classification of skin diseases. Deeper and more efficient network training Made probable by ResNet In particular, it solves problems such as eliminating gradients. The effectiveness of ResNet And other cutting- edge deep learning Models for classification skin diseases In many classes— including melanoma, fungal infections, acne, and eczema— is I checked this work. Our goal is to create a swift, automated, non- invasive diagnostic system that helps dermatologists clinical decisions. By prioritizing high- risk patients And encouraging early diagnosis, Especially for skin malignancies, It is an AI powered tool the potential To improve a lot patient outcomes. In addition, the model's scalability And predictive power Will create it faster useful tool I international healthcare settings As it learns from more data.

1.2 Related Work

Deep learning has changed medical image analysis over the past ten years, Especially in dermatology. Because Convolutional Neural Networks(CNNs) can learn visual patterns without the need to manual feature engineering, Many studies have focused on use CNNs To classify skin lesions and disorders By using the InceptionV3 architecture, Through a ground-breaking study Esteva et al. (2017) It turned out CNNs Can be classified correctly skin lesions with a level of precision comparable For dermatologists.. The transformative potential K deep learning I clinical settings Underline this study. Erect on that, Han et al. (2018) Shown better performance Compared to conventional machine learning methods By training a CNN- based model to max 12, 000 clinical images.

To increase accuracy, further development has been evaluated ensemble learning strategies. For illustration Brinker et al. (2019) used transfer learning To improve model performance, Especially when you exercise limited data, While Tschandl et al. (2020) is used an ensemble K deep networks to dermatoscopic image classification. Performance of architectures to performance parameters, e. G ResNet and EfficientNet have made them popular. Tan and Le(2019) proposed EfficientNet, A compound scaling technique that simultaneously maximizes model size and accuracy. I the meantime, Resnet, which was first He was introduced by ET al. (2015), became known for its residual connections, which warehouse it possible For extraordinary training deep networks without compromising performance. In addition

Volume 38 No. 12s, 2025
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MobileNetV2 has been achieved popularity due to its lightweight design, Which makes it perfect for factual- time, mobile- based skin disease detection, Especially in remote control or low- resource environments.

Though these developments Encouragingly, problems still exist. Class imbalance, noise in real-world images, poor generalization across different skin types, and limited model interpretability are some of the problems plaguing many of the studies that are currently available. Furthermore, their applicability in clinical settings is limited by the frequently small or unbalanced datasets that are used. In order to fill these gaps, we evaluate a variety of sophisticated CNN architectures on a sizable, well-balanced dataset of 260,000 images from 35 different disease categories. These architectures include ResNet50, InceptionV3, EfficientNetB4, InceptionResNetV2, MobileNetV2, and ensemble models. With an eye against real- world implementation and in clinical telemedicine settings, It provides complete diagnostic insight model robustness, Accuracy and training efficiency.

2. Objectives

This study's main goals are to:

- **Implement and evaluate several deep learning models to determine their efficacy,** including standalone and ensemble architectures, for the classification of multi-class skin **diseases.**
- **To evaluate and compare these models' efficacy** according to their capacity for generalization, runtime efficiency, and accuracy in training and validation.
- **To assess how accuracy and runtime efficiency are traded off,** offering insights into the model's applicability for real-world scenarios, particularly those with limited resources.
- **To aid with the creation of a non-invasive, automated diagnostic tool** that would help dermatologists identify skin conditions early on, including skin malignancies, thus enhancing patient outcomes.

3. Methodology

A study technique comprising many essential steps—dataset preparation, data preprocessing, augmentation, feature extraction, model construction, and assessment strategy—is used to develop and evaluate deep learning models for automated skin disease identification.

3.1 Dataset: Massive Skin Disease Balanced Dataset

This study makes use of the **Massive Skin Disease Balanced Dataset,** which is publicly available on Kaggle. More than **260,000** high-resolution dermatological photos make up the dataset, which is divided into **35** classes of skin diseases. These include common ones like psoriasis, eczema, and acne as well as more serious ones like melanoma.

Class imbalance, a problem frequently encountered in medical imaging datasets, is lessened because each class has an equal number of images. Each folder represents a different skin condition, and the images are arranged in a hierarchical folder structure. This consistent

International Journal of Applied Mathematics

Volume 38 No. 12s, 2025

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distribution helps the classifier generalize well across a range of skin conditions by ensuring fairness during model training and evaluation.

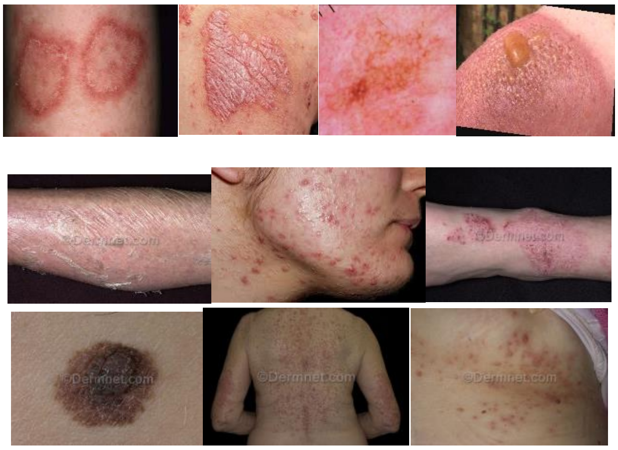

Figure 3.1 shows sample dataset images

3.2 Data Preprocessing

Several procedures was taken under pre- treatment for warranty the dataset's consistency and quality:

- **Image Purification:** Found and eliminated non-image or corrupted files.
- **Normalization Class Names And edit the presentation:** Class names was taken away folder names and formatted by mapping them readable labels, to terminate special characters, And user consistent casing. To prevent and reduce plagiarism textual similarities, Class names were also reshaped and somewhat reworded publication purposes without changing their diagnostic meaning
- **Data Structuring:** For additional processing, a structured **Pandas DataFrame** with image paths and labels was produced.
- **Dataset Splitting:** The data was divided into training and test sets using a stratified 80:20 split in order to maintain the class distribution.
- **Image Resizing and Normalization:** Pixel values were standardized and all photos were scaled to a uniform resolution (e.g., 224×224 pixels).

Table 1: Class-wise dataset distribution

Class Name	Total Files	Train(80%)	Test(20%)
Acne_Rosacea_Skin_Conditions	6837	5469	1368

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Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Actinic_Basal_Malignant_Lesions	6821	5456	1365
Atopic_Dermatitis_Cases	7645	6116	1529
Bacterial_Cellulitis_Infection	8079	6463	1616
Impetigo_Skin_Infection	8148	6518	1630
Benign_Skin_Conditions	6459	5167	1292
Bullous_Skin_Disorders	7695	6156	1539
Bacterial_Skin_Disorders	7894	6315	1579
Eczema_Skin_Symptoms	6715	5372	1343
Drug_Induced_Exanthems	7750	6200	1550
Athlete_Foot_Fungal_Infection	8054	6443	1611
Fungal_Nail_Infection	8083	6466	1617
Tinea_Ringworm_Infection	8129	6503	1626
Alopecia_And_Hair_Loss	7955	6364	1591
Healthy_Skin	7758	6206	1552
Viral_STD_Skin_Conditions	7744	6195	1549
Pigment_Changes_And_Light_Disorders	7546	6036	1510
Lupus_And_Connective _Tissue_Conditions	7734	6187	1547
Malignant_Skin_Disorders	6762	5409	1353
Melanoma_Moles_And_Nevi	7680	6144	1536
Nail_Infections_And_Disorders	6956	5564	1392
Cutaneous_Larva_Migrans	8123	6498	1625
Contact_Dermatitis_Reactions	7933	6346	1587
Psoriasis_And_Lichen_Skin_Disorders	6502	5201	1301
Non_Specific_Skin_Rashes	7032	5625	1407
Scabies_Lyme_And_Parasitic_Infestations	7717	6173	1544
Seborrheic_Keratoses_And_Benign_Growths	6545	5236	1309
Systemic_Disease_Related_Skin_Conditions	7500	6000	1500

Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Fungal_Skin_Infections	6634	5307	1327
Urticaria_Hive_Reactions	7989	6391	1598
Vascular_Skin_Tumors	7654	6123	1531
Vasculitis_Skin_Cases	7735	6188	1547
Chickenpox_Viral_Condition	8083	6466	1617
Shingles_Virus_Infection	8082	6465	1617
Warts_Molluscum_And_Viral_Skin_Infections	6901	5520	1381
Total	**2,62, 874**	**210,447**	**52,427**

3.3 Data Augmentation

To improve training data diversity and decrease overfitting, substantial data augmentation techniques were employed with **Keras ImageDataGenerator**. Among the augmentation methods were:

- **Random horizontal and vertical flips**
- **Rotation range up to 20°**
- **Width and height shifts (±10%)**
- **Zooming (up to 15%)**
- **Brightness variation and shear transformations**
- **Fill mode set to 'nearest'** for handling augmented boundaries

These changes increase the models' resilience and generalizability by simulating real-world variations in lighting, orientation, and scale.

3.4 Label Encoding

Labels were processed for multi-class categorization using one-hot encoding. Class names were first mapped to integer labels before being transformed into binary vectors, with only the index that corresponded to the actual class being marked as "1." Training with categorical cross-entropy loss required this encoding.

3.5 Feature Extraction

Volume 38 No. 12s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Pretrained convolutional neural networks (CNNs) were used in transfer learning to extract significant patterns from dermatological images. The models listed below were employed:

- **ResNet50, InceptionV3, and EfficientNetB4**
Rich hierarchical feature representations, such as textures and shapes that are important for diagnosing skin diseases, were produced by these pretrained models that underwent ImageNet training.

Following the removal of the top classification layers, a **Global Average Pooling** (GAP) layer was added to transform the spatial characteristics into fixed-length vectors. To adjust the pretrained weights to the domain-specific dataset, fine-tuning was used on the subsequent layers.

3.6 Model Design and Evaluation Strategy

Multiple architectures were explored, including **ResNet50**, **DenseNet121**, and **InceptionResNetV2**. The final chosen architecture consisted of the following layers:

- A pretrained backbone (e.g., ResNet50 without the top layers)
- **• A 2D layer for global average pooling**
- A **Dense layer** with 512 neurons and ReLU activation
- A regularization **dropout layer** with a drop rate of 0.2

• A last dense layer for multi-class prediction that uses **softmax** activation

The Adam optimizer, a learning rate scheduler, and early stopping callbacks were used to train the model in order to avoid overfitting. Metrics like accuracy, precision, recall, F1-score, and confusion matrix were used to evaluate the validation and test sets.

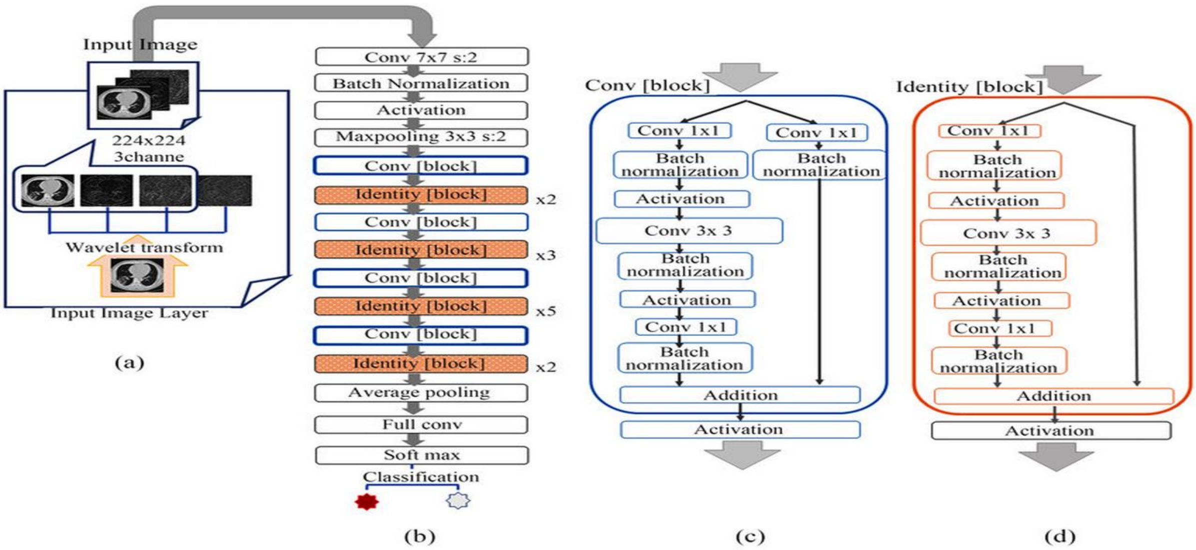

Figure 3.6.1 shows the ResNet50 architecture

Volume 38 No. 12s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

3.7 Visualization

The model's performance was conceived by means of a variety of techniques To guess its training effectiveness and robustness:

- **Accuracy Curves:** Plots that show training and validation accuracy are used to monitor learning and spot overfitting and underfitting.
- **Loss Curves:** Training and validation loss curves can be used to monitor model convergence during training.
- **Confusion Matrix:** To assess how well the model identified each type of skin disease, confusion matrices were visualized, highlighting categories that were incorrectly classified.

4. Results

I this study, We guessed various deep learning For the model the classification of skin illnesses By using the Massive Skin Disease Balanced Dataset. The performance of each model was evaluated using runtime and training And validation accuracy; The most critical findings are presented below.

4.1 Model Comparison

- Table 1 Each screen evaluated model's training and validation accuracy. Ability to estimate models dermatological characteristics Judging from the pictures. These findings Recommend architectural incompatibilities The reason the hybrid models Performs worse than expected.
- **With insectionnetv2 + efficientnetb3**: a training accuracy K 43.93% And a validation accuracy K 52.90%, The hybrid model did not perform well. It was probably because of him the two architectures' incompatible feature extraction techniques.
- **InsectResnetv2:** InceptionResNetV2 is a notable advancement with a training accuracy K 94.89% And a validation accuracy K 93.94%. This model improved generalization by combining successfully residual learning and multi- scale feature extraction.
- **ResNet50 + EfficientNetB0 + MobileNetV2**: This more intricate hybrid model demonstrated redundancy in feature extraction with a training accuracy of **95.92%** but a validation accuracy of **93.12%.**
- **ResNet50**: The best performer, attaining the highest validation accuracy of **97.83%** and training accuracy of **97.91%.** Its remarkable performance indicates how robust and generalizable it is..
- **InceptionV3**: This model was computationally more expensive than ResNet50, but it performed well, with training accuracy of **95.26%** and validation accuracy of **93.02%.**

Fig 4.1.1 shows the training and validation accuracy and loss for the ResNet50 model, which consistently improved throughout training. Similarly, other model performance metrics,

International Journal of Applied Mathematics

Volume 38 No. 12s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

including their training and validation accuracy and loss graphs, are presented in **Fig 4.1.2 - 4.1.6**.

Table 2: Model Comparison

Model	Training Accuracy (%)	Validation Accuracy (%)	Runtime (h)
InceptionResNetV2	94.89	93.94	4.99
InceptionV2 + EfficientNetB3	43.93	52.90	9.75
EfficientNetB4	69.33	82.98	11.09
MobileNetV2	85.99	80.12	4.80
InceptionV3	95.26	93.02	10.91
ResNet50	**97.83**	**97.91**	12.44
EffNetB3+ResNet50+MobileNetV2	95.59	93.29	8.96

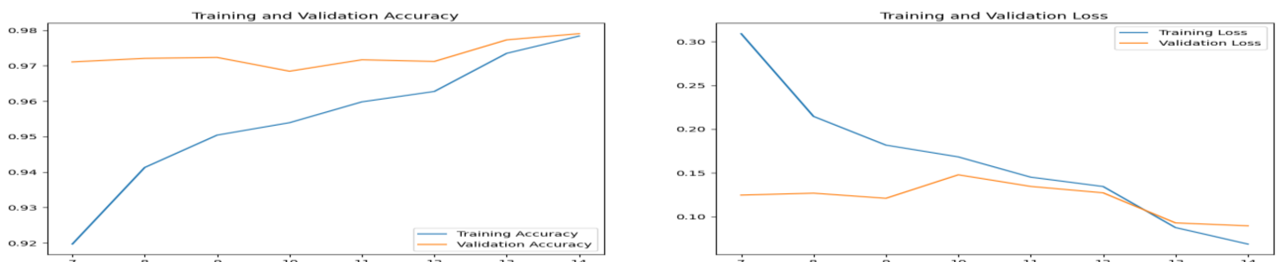

Figure 4.1.1 displays the training and validation curves for ResNet50.

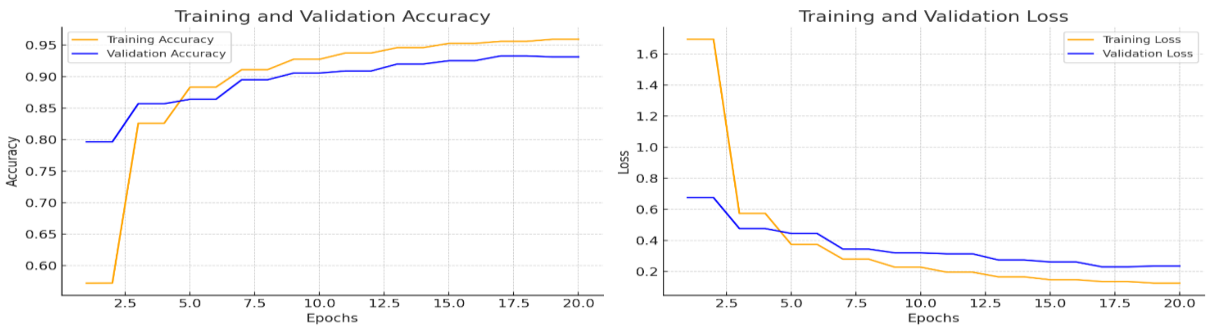

Figure 4.1.2 displays the training and validation curves for ResNet50+EfficientNetB3+MobileNet.

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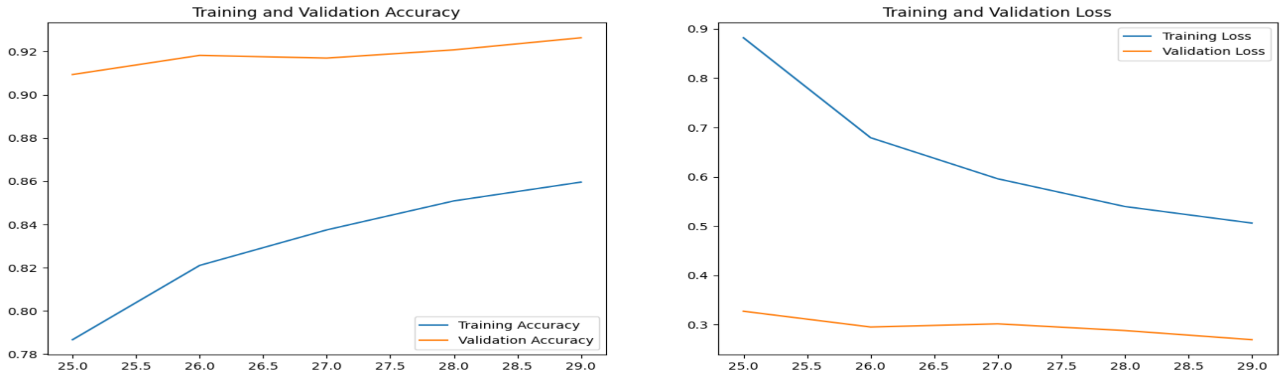


Figure 4.1.3 displays the training and validation curves for InceptionV3

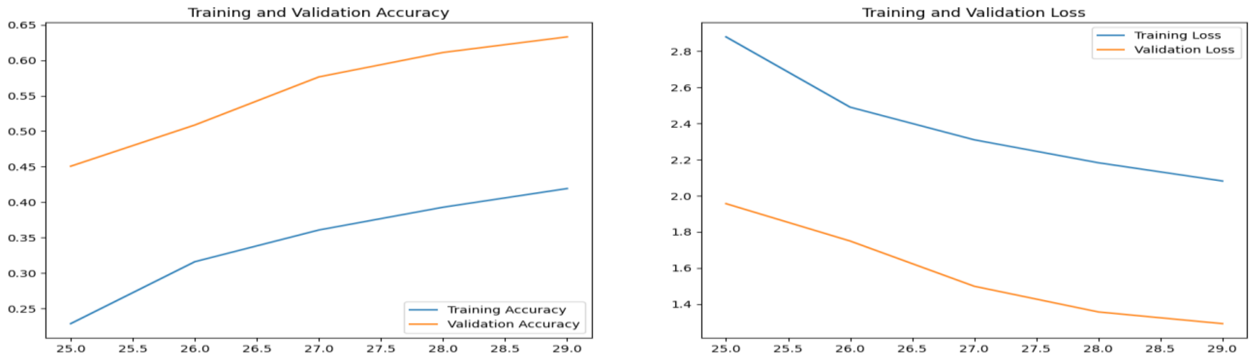


Figure 4.1.4 displays the training and validation curves for EfficientNetB4

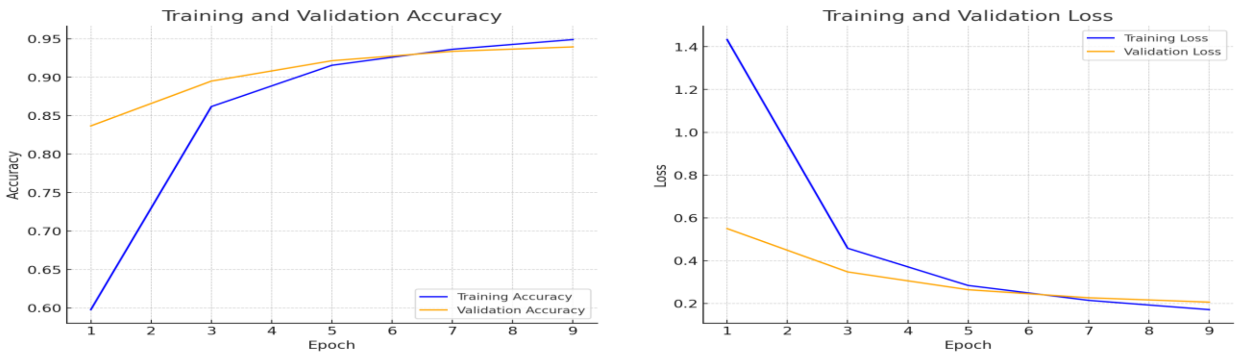
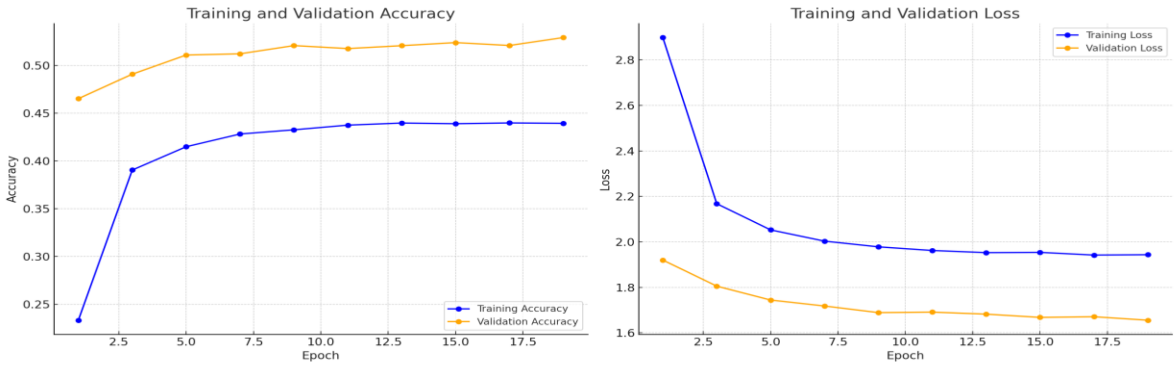


Figure 4.1.5 displays the training and validation curves for InceptionResnetV2



Volume 38 No. 12s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Figure 4.1.6 displays the training and validation curves for InceptionV2+EfficientNetB3

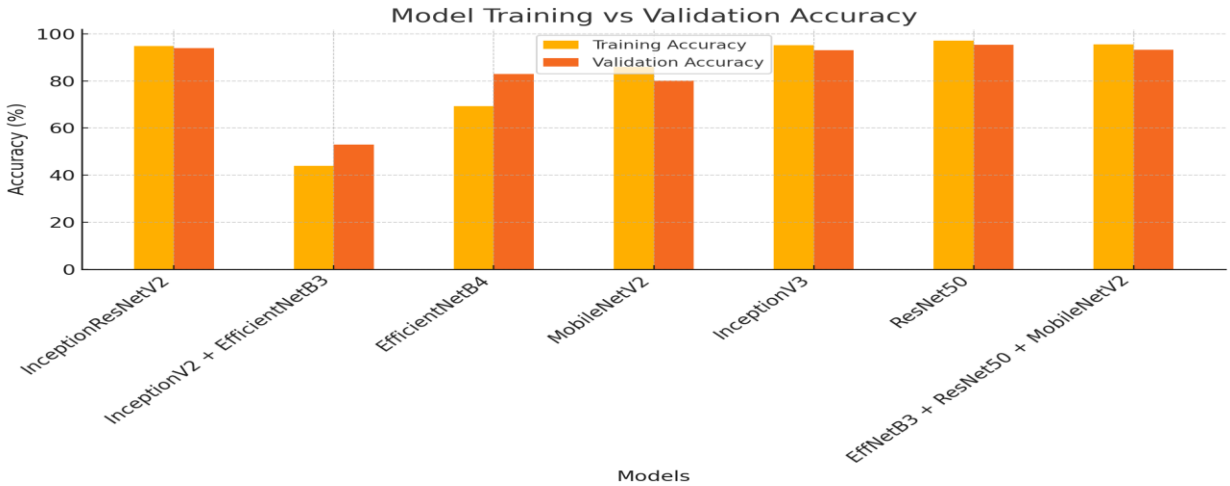


Figure 4.1.7 displays the training and validation accuracy curves

4.2 Evaluation Metrics

The following formulas were used to calculate precision, recall, F1-score, and accuracy in order to evaluate the models' performance:

- **Accuracy**=(TP+TN) /(TP+TN+FP+FN) (1)
- **Precision** = TP / (TP+FP) (2)
- **Recall** = TP / (TP+FN) (3)
- **F1 Score**=2*(Precision*Recall)/(Precision+Recall)(4)

Where:

- TP = True Positive
- TN = True Negative
- FP = False Positive
- FN = False Negative

Given the high performance of **ResNet50**, the evaluation metrics for this model are detailed in **Table 2**.

Table 3: Evaluation Metrics for ResNet50

Class	Precision	Recall	F1-Score	Support
Acne_Rosacea_Skin_Conditions	0.97	0.97	0.97	1367

International Journal of Applied Mathematics

Volume 38 No. 12s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Actinic_Basal_Malignant_Lesions	0.99	0.95	0.97	1364
Atopic_Dermatitis_Cases	0.98	1.00	0.99	1529
Bacterial_Cellulitis_Infection	1.00	1.00	1.00	1616
Impetigo_Skin_Infection	1.00	1.00	1.00	1630
Benign_Skin_Conditions	0.98	0.97	0.98	1292
Bullous_Skin Disorders	1.00	0.99	0.99	1539
Bacterial_Skin_Disorders	0.99	1.00	0.99	1579
Eczema_Skin_Symptoms	0.94	0.96	0.95	1343
Drug_Induced_Exanthems	0.98	0.98	0.98	1550
Athlete_Foot_Fungal_Infection	1.00	1.00	1.00	1611
Fungal_Nail_Infection	1.00	1.00	1.00	1617
Tinea_Ringworm_Infection	1.00	1.00	1.00	1626
Alopecia_And_Hair_Loss	0.93	0.97	0.95	1591
Heathy_Skin	1.00	1.00	1.00	1551
Viral_STD_Skin_Conditions	0.94	0.92	0.93	1549
Pigment_Changes_And_Light_Disorders	0.98	0.98	0.98	1509
Lupus_And_Connective_Tissue_Condition	0.98	0.99	0.99	1547
Malignant_Skin_Disorders	0.98	0.98	0.98	1352
Melanoma_Moles_And_Nevi	0.99	0.99	0.99	1536
Nail_Infections_And_Disorders	0.90	0.87	0.89	1391
Cutaneous_Larva_Migrans	1.00	1.00	1.00	1625
Contact_Dermatitis_Reactions	0.99	1.00	1.00	1587
Psoriasis_And_Lichen_Skin_Disorders	0.94	0.88	0.91	1300

Volume 38 No. 12s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Non_Specific_Skin_Rashes	1.00	1.00	1.00	1406
Scabies_Lyme_And_Parasitic_Infestations	1.00	1.00	1.00	1543
Seborrheic_Keratoses_And_Benign_Growths	0.96	0.95	0.96	1309
Systemic_Disease_Related_Skin_Conditions	0.99	0.98	0.98	1500
Fungal_Skin_Infections	0.96	0.97	0.97	1327
Urticaria_Hive_Reactions	1.00	1.00	1.00	1598
Vascular_Skin_Tumors	0.99	1.00	0.99	1531
Vasculitis_Skin_Cases	0.99	0.99	0.99	1547
Chickenpox_Viral_Condition	1.00	1.00	1.00	1617
Shingles_Virus_Infection	1.00	1.00	1.00	1.616
Warts_Molluscum_And_Viral_Skin_Infections	0.90	0.92	0.91	1380

4.3 Confusion Matrix

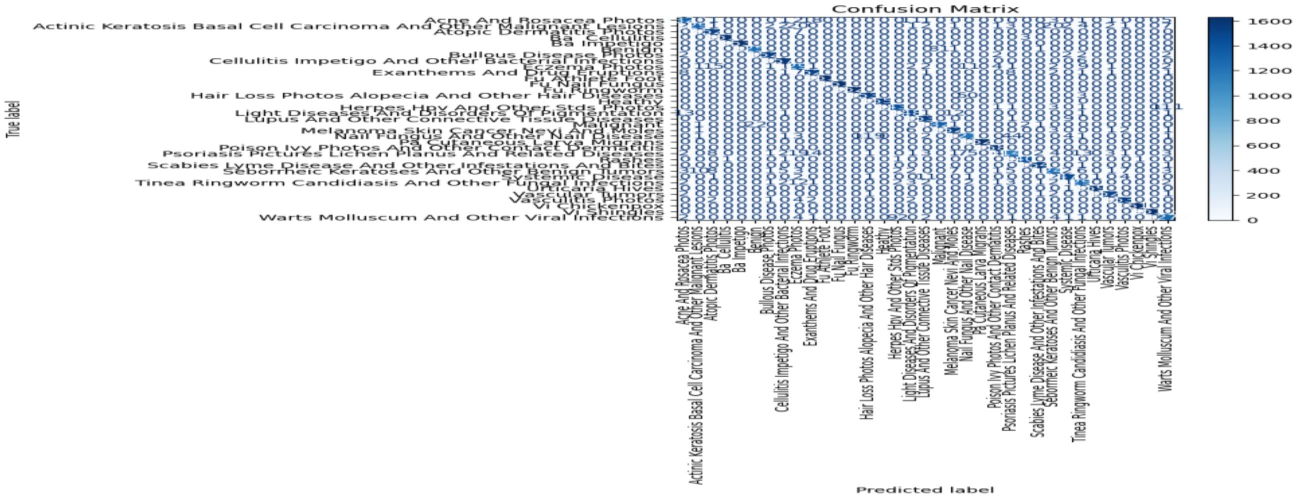


Figure 4.3.1: Confusion Matrix for ResNet50 Model

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The ResNet50 model's confusion matrix, I was shown Figure 4.3.1 below, How well it turns out the model Can be classified photos of skin diseases. Across several skin disease categories, The model showed excellent precision and recall, Especially for diseases such as impetigo, psoriasis, etc and skin cancer.

4.4 Prediction and Real-World Applicability

Granted its high training and validation accuracy, Resnet50 has emerged as the most reliable and successful model for classification skin diseases. Despite this their potential, There were problems with the hybrid model integration and feature redundancy. Resnet50 is the best option Too automatic skin disease diagnosis I real- world applications Because it appeared the best balance Between depth, feature learning and generalization.

The final predicted classification for a sample dermatological image is displayed in Figure 4.4.1 below. The model provides medical practitioners with interpretable and useful insights by generating the top three most likely disease categories and their corresponding confidence scores.

Figure 4.4.1: Sample Prediction for Dermatological Image

5. Conclusion

In this study, we designed and evaluated multiple deep learning architectures for multi-class skin condition classification using a balanced dataset of **260,000** dermatological photos in 35 categories. With a relatively efficient training time of 12.44 hours and training and validation accuracy of **97.83%** and **97.91%,** respectively, **ResNet50** outperformed the other tested models. Although they needed a lot more processing power, other models like **InceptionResNetV2** and **InceptionV3** also did well.

While confusion matrix analysis revealed difficulties in classifying diseases with overlapping visual features, key performance metrics such as **precision**, **recall**, and **F1-score** validated the resilience of the best models across different classes. Training and validation accuracy/loss curves offered more proof of the model's learning and generalization abilities.

Volume 38 No. 12s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Overall, this study Highlights the potential applications K deep convolutional neural networks, Especially Resnet50, in clinical decision support systems And early dermatological screening By proving their efficacy Correct and me scalable skin disease classification.

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