

## SKIN DISEASE DETECTION USING CNN MODEL

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**Abstract** - Skin diseases are one of the most common problems with human health around the world, affecting millions of individuals each year. Early and accurate diagnosis is extremely important in timely treatment and management. This project presents a deep learning-based system for automatic classification of skin diseases using convolutional neural networks (CNNs) that folds the MobilenetV2 as the base model. The data record consists of eight different classes of skin infections, including bacteria, fungi, parasitic and viral diseases. Images are subject to preprocessing steps such as resizing, normalization, and labeling coding to ensure consistency and optimal performance. The proposed framework reaches 97% accuracy and demonstrates its potential as an efficient and reliable means of supporting dermatologists in the diagnosis of skin diseases.

**Key Words:** Skin Disease Detection, Convolutional Neural Network (CNN), MobileNet V2, Deep Learning, Image Classification, Medical Diagnosis, Artificial Intelligence, Accuracy 97%.

### 1. INTRODUCTION

The skin is the largest organ of the human body, playing a crucial role as a protective barrier against bacteria, viruses, germs, and harmful ultraviolet (UV) radiation. Beyond protection, it performs several vital functions such as regulating body temperature, enabling the sensation of touch, and contributing to overall physical appearance. Healthy skin not only reflects good health but also significantly boosts self-confidence. Yet skin, while being important, is the subject of many diseases, most of which are increasingly common in today's world. There are some highly contagious skin conditions which have a very big public health impact. On many occasions, people miss their first dose or delay treatments in the early stages of cancer development because they are unaware or cannot afford treatment or they are too busy. If that is, negligence often leads to more serious complications, even life threatening ones, such as skin cancer. A lot of awareness needs to be raised concerning skin health, early diagnosis, and getting timely treatment with a view to avoiding such outcomes. In the case of skin care, I am happy to say that prioritizing it and acknowledging the importance of it as an important organ could lead to healthier lives and lessen skin disease burden on individual as well as the healthcare system.

Each year, about 900 million people around the world have skin diseases – from simple conditions like acne to psoriasis

and skin cancer, a WHO report says. In 2019, there were 4,859,267,654 new cases of skin and subcutaneous diseases (95% UI 4,680,693,440–5,060,498,767 cases) worldwide, of which bacterial and fungal skin diseases comprised the bulk of the new cases. A fourth make up 34% and fifth accounted for 23% of the total [1].

According to the report, "4,859,267,654 (95% uncertainty interval [UI], 4,680,693,440–5,060,498,767) new skin and subcutaneous disease cases that were identified, most were fungal (34.0%) and bacterial (23.0%) skin diseases, which accounted for 98,522 (95% UI 75,116–123,949) deaths. The burden of skin and subcutaneous diseases measured in DALYs was 42,883,695.48 (95% UI, 28,626,691.71–63,438,210.22) in 2019, 5.26% of which were years of life lost, and 94.74% of which were years lived with disability" (Yakupu et al., 2023) [1].

We have seen the growth of many technologies as medical science has advanced and many of these have enabled us to better diagnose those skin diseases. Despite this, many derms still depend on manual inspection to spot skin conditions. Though this archetypical approach shall always be the option of many practitioners, it isn't flawless. It is a time consuming, menial and prone to human error, manual diagnosis. The outcome of which is that despite the complexity of certain dermatological conditions, it is not uncommon that different specialists come to very different conclusions about a diagnosis or treatment plan.

A combination of clinical experience with unpredictable skin presentations may make the continued reliance on blind manual examination a reality. Skepticism towards fully automation has also been provoked by these factors. Though the potential benefits for integration of computer based diagnostic tools into dermatology may not be so obvious, the potential benefits are worthwhile. They also available in automated systems, much faster and more accurate in diagnosis with artificial intelligence (AI) and machine learning (ML) involved. With access to huge amounts of data, these models are able to identify delicate patterns that may be passed over for the human eye, helping to lower diagnostic mistakes and variety.

Rather, the goal of AI/ML systems would be to act as a powerful decision support tool rather than replacing dermatologists. They might help clinicians make more consistent and precise diagnoses, ultimately helping patients. These technologies can become novel research

elements in dermatology when their components are integrated together properly. Automated diagnostic tools complement rather than replace traditional methods, bridging between human expertise and capacity to perform more routine tasks.

An automation integration into the diagnostic process has the potential to transform future outcomes. In addition to the ability to revolutionize detection of skin diseases, it has the potential to improve overall patient care standards, as well as meeting healthcare delivery needs. Stepping toward these advancements better means a more speeds up and more dependable dermatological practice, one that exploits the strengths of each human in addition to computational exactness.

## 2. LITERATURE SURVEY

Skin diseases irritate millions of people around the world. Early detection benefits the patient outcomes and relieves health care systems of a burden. In recent years, more researchers have been using deep learning—as a branch of artificial intelligence—to build automated systems to spot and classify skin diseases in medical images. Designed to assist dermatologists in improving accuracy and efficiency in dermatologic diagnostic procedures, these systems aim to reduce the delays caused by the time required for biopsy processing and reporting to initial diagnosis.

In this paper, we review state of the art for deep learning for skin disease prediction. It looks at the use of different methodologies in recent studies, convolutional neural networks in particular as well as other advanced AI models. A review of distributed SML is provided along with the discussion of some ongoing challenges facing the technologies, including data quality, variability in skin presentation, and the requirement of large and diverse datasets for training robust models. Moreover, it explores what future research should entail, including embedding the AI tools in a clinical setting and how to implement these tools in an ethical and transparent way. Finally, overall, deep learning could enable a revolution in the diagnosis of skin disease, and subsequent improvements in patient care.

1. Ki V., Rotstein C. proposed the work [2] on Bacterial skin and soft tissue infections in adults: The epidemiology, pathogenesis, diagnosis, and treatment of infections are reviewed herein. Likely pathogens, route of entry, disease severity, and associated clinical complications will determine the selection of antimicrobial therapy. Knowledge of these factors is important for treatment and improved patient outcomes for infectious diseases, including proper therapeutic strategies.
2. Sae-lim W., Wettayaprasit W., Aiyarak P [3] presented a skin lesion classification approach based on the light weight deep Convolutional Neural Networks (CNNs),

called MobileNet. They employed MobileNet and proposed the modified MobileNet for skin lesion classification.

3. Bandyopadhyay et al. [4] proposed a model by combining deep learning (DL) and machine learning (ML). Deep Neural Networks (AlexNet, GoogleNet, ResNet50, and VGG16) were used to perform feature selection. Models of Support Vector Machine, Decision Tree, and Ensemble Boosting (AdaBoost) were used for classification. For this reason, a comparative analysis was carried out to compare and identify the most effective prediction model to predict the optimal combination of inputs for high classification performance.
4. Maduranga et al. [5] presented an artificial intelligence (AI) based mobile application for the detection of skin diseases. To classify skin diseases, they used Convolutional Neural Networks (CNN) on the HAM10000 dataset. Additionally, they used MobileNet with transfer learning to create a mobile application for fast and precise recognition, achieving an accuracy of 85%.
5. Shanthi et al. [6] proposed a method to detect four types of skin diseases using computer vision. For the proposed method, convolutional neural networks (CNNs) comprising about 11 layers - Convolution, Activation, Pooling, Fully Connected, and Softmax Classifier - are used. We validate this architecture with care data from the DermNet database, recognizing samples of 30 to 60 different skin conditions. Though the focus here is in four core categories: eczema herpeticum, urticaria, keratosis, and acne. With this, we get an impressive accuracy between 98.6% and 99.04%.

A Python-based AI and computer vision system for diagnosing and identifying skin conditions. Oversaw the whole project pipeline, including the collection of data, pre-processing, and model training. shown proficiency with deep learning and machine learning approaches by using Keras, TensorFlow, OpenCV, and other libraries for CNN models and image processing.

## 3. PROPOSED SYSTEM

In this thesis, a system for skin disease diagnosis is proposed based on advanced deep learning methods and effective data preprocessing techniques. The core of the system is the pre trained MobileNet V2 model, a lightweight architecture model with high performance on image classification tasks. In this work, the discriminative features of input medical images are extracted using MobileNet V2 and using the extracted features, eight different types of skin diseases are classified accurately. For the robustness and versatility of the model across different datasets, a thorough

preprocessing pipeline is developed. These include the most basic steps of the training which are image resizing and image normalization to standardize input and typically improve performance by reducing variability. They're going to allow the model to generalize better across different image sources, different image quality levels and it also makes sure that the results allow the same result every time.

Figure 1 shows the system architecture, which brings together all components—data acquisition, preprocessing, feature extraction, and disease classification—on a unified platform. With this holistic design, efficient operation, scalability, and simple field deployment is enabled for clinical environments.

The system combines a powerful, very lightweight deep learning model combined with optimized data handling to provide a practical and effective automated skin disease diagnosis solution. User can efficiently reduce time and effort for medical professionals to reach a diagnosis and enhances diagnostic accuracy. Additionally, it may be used more broadly in both telemedicine and remote healthcare contexts where specialized dermatological expertise may be unavailable. In short, the proposed system shows how (appropriately) combining modern AI tools with good data processing can take the field of dermatology forward considerably. Not only does it helps clinician diagnose faster and more accurate, it also improves patient care and healthcare efficiency.

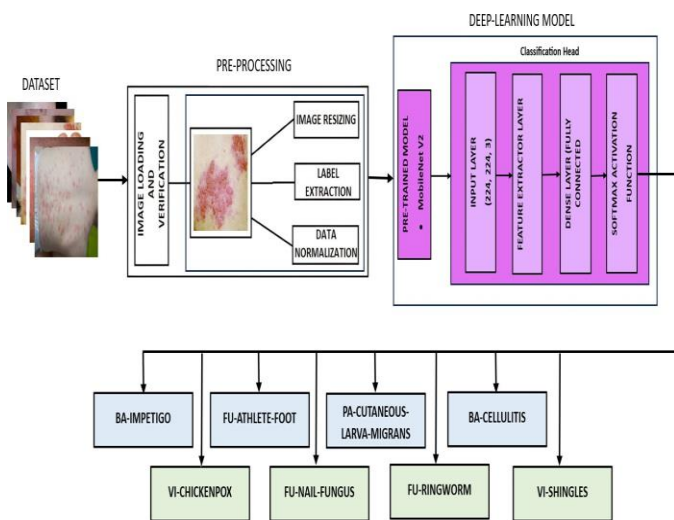


Figure-1: Block Diagram of the Proposed Model

A. Deep Learning Model Construction:

A Convolutional Neural Network typically has three layers.

1) *Input Layer*: Suppose the image has 32 width and 32 height and R, G, and B color channels, it will retain the image's raw pixel([32x32x3]) values.

2) *Convolution Layer*: This layer computes the results of neurons attached to nearby input components. A dot product between weights and a tiny region in the input volume that they are really connected to is calculated by each neuron. For example consider, if we decide to use 12 filters, the volume will be [32x32x12].

3) *ReLU Layer*: This layer is used to apply a pointwise activation function, for example,  $\max(0, y)$  thresholding as 0. The result ([32x32x12]) corresponds to volumes of the same size.

4) *Pooling layer*: This layer is used to perform a down-sampling operations along the spatial dimensions, which results in a volume of [16x16x12].

5) *Locally Connected Layer*: After receiving an input from the previous layer, this typical neural network layer calculates the class scores and produces a 1-Dimensional array that is equal to the number of classes. Next, we will add a Pooling layer to our Convolutional layer so that each feature map may be combined into a Pooled feature map. Ensuring spatial invariance in our images is the primary goal of the pooling layer. It also helps us reduce the size of our photos and prevent overfitting of our data. After flattening all of our pooled photos into a single long vector or column, we will next feed all of these values into our artificial neural network.

B. Dataset and Dataset Handling:

Certain pathogens, like fungi and bacteria, are normally found on the skin, but when they multiply too much, the immune system is unable to control them. In this case, an infection can result. The microorganism responsible for a skin disease determines its root cause.

Here I am using the dataset of skin diseases from Kaggle:

(<https://www.kaggle.com/datasets/subirbiswas19/skin-disease-dataset>)

The dataset used in this study was sourced from Kaggle and contains labeled images representing eight categories of skin diseases. The dataset is organized in a structured folder format, where each folder corresponds to a specific disease type. This structure facilitates straightforward image-label mapping for training purposes. The dataset includes infections caused by bacteria (cellulitis, impetigo), fungi (athlete's foot, nail fungus, ringworm), parasites (cutaneous larva migrans), and viruses (chickenpox, shingles).

This dataset directory is arranged into a structured hierarchy, with each subdirectory representing a distinct disease category.

The dataset contains total of 8 classes, which are as follows

1. Bacterial Infections- cellulitis
2. Bacterial Infections- impetigo
3. Fungal Infections - athlete -foot
4. Fungal Infections - nail-fungus
5. Fungal Infections - ringworm
6. Parasitic Infections - cutaneous-larva-migrans
7. Viral skin infections – chickenpox
8. Viral skin infections – shingle

**C. Data Pre-processing:**

1) *Image Loading and Verification:* Pictures are loaded into memory from the dataset directory. Image verification is done to find and deal with any corrupted or unreadable images in order to guarantee data integrity.

2) *Image Resizing:* Every image is resized into 224x224 pixels, which is a standard size. This size procedure aims to normalize image dimensions and promote consistency through datasets.

3) *Label Extraction:* The subfolder structure in directory provides labels for each image combining each image with a specific disease group. Disease categories contain numerical identifiers.

4) *Data Normalization:* The pixel values of the created images are normalized to be classified into the range 0-1. This normalization procedure prevents any of the characteristics from controlling the model's learning process.

**D. Deep Learning Model Construction:**

1) *Pre-Trained Model Utilization:* The classification model is entirely based on a pre-trained deep learning version known as MobileNet V2. This pre-trained version is initialized with weights learned from large image datasets and provides useful feature extraction capabilities.

2) *Input Layer:* The model design has an entry layer with a fixed input shape of 224x224x3. This level guarantees compatibility with the feature extractor and acts as an entrance factor for images.

3) *Feature Extractor Layer:* The pre-trained feature extractor layer, MobileNet V2, is integrated into the model architecture. This layer extracts relevant

features from the input image and captures discriminatory information for disease classification.

4) *Output Layer:* An output layer with SoftMax activation is added to the model. This layer consists of eight neurons corresponding to eight disease classes. SoftMax activation calculates probability distributions through disease classes and promotes multi-class classification.

**E. Model Training:**

1) *Compilation:* The model is compiled with loss and optimization functions namely sparse categorical cross entropy loss and Adam optimizer, respectively are used for multi-class classification.

2) *Training:* The compiled model is trained iteratively on pre-processed training data. During training, model parameters are adjusted based on computed loss to minimize prediction errors. The optimization process continues for multiple epochs until convergence is achieved.

**4.PERFORMANCE ANALYSIS**

**A. Experimental Setup:**

The experiment includes two deep learning models, MobileNet and InceptionV3 on the data records to train and evaluate, including images of various skin diseases. The dataset consisted of a total of 1159 samples from eight different classes, including cellulitis, impetigo, athlete's foot, nail fungus, ringworm, cutaneous larva migrans, chickenpox, and shingles. I prepared the photos and changed them to meet the input format of each model. The performance of the model was assessed using standard rating metrics, including accuracy, loss, precision, recall, and F1-score

**B. Model Evaluation:**

The performance of the MobileNet and InceptionV3 models was evaluated using a held-out test set. Fig. 2 shows classification reports for both models:

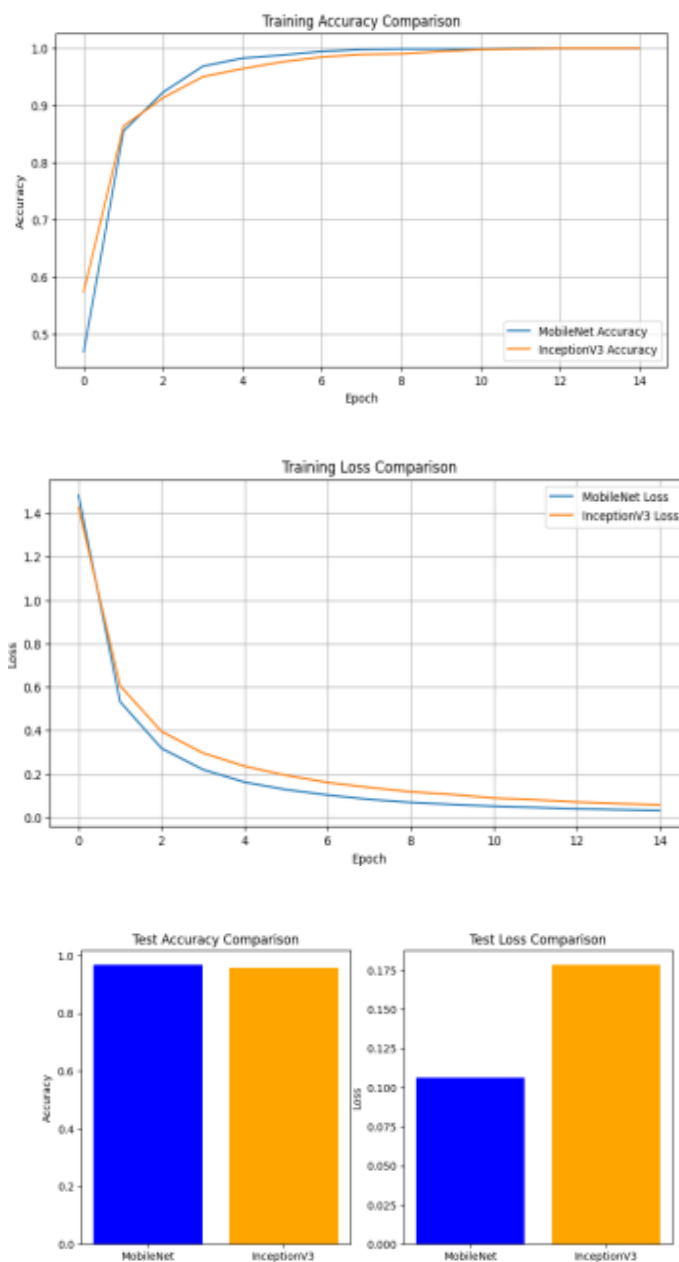
MobileNet Classification Report:					InceptionV3 Classification Report:				
	precision	recall	f1-score	support		precision	recall	f1-score	support
0	1.00	0.94	0.97	34	0	0.92	0.97	0.94	34
1	0.95	1.00	0.98	20	1	0.90	0.95	0.93	20
2	0.91	0.94	0.92	32	2	1.00	0.91	0.95	32
3	0.97	0.97	0.97	33	3	1.00	1.00	1.00	33
4	0.96	1.00	0.98	23	4	1.00	0.83	0.90	23
5	0.96	0.92	0.94	25	5	0.89	1.00	0.94	25
6	1.00	1.00	1.00	34	6	1.00	0.97	0.99	34
7	1.00	1.00	1.00	33	7	0.94	1.00	0.97	33
accuracy			0.97	234	accuracy			0.96	234
macro avg	0.97	0.97	0.97	234	macro avg	0.96	0.95	0.95	234
weighted avg	0.97	0.97	0.97	234	weighted avg	0.96	0.96	0.96	234

**Figure-2: Classification Report for MobileNet and InceptionV3**

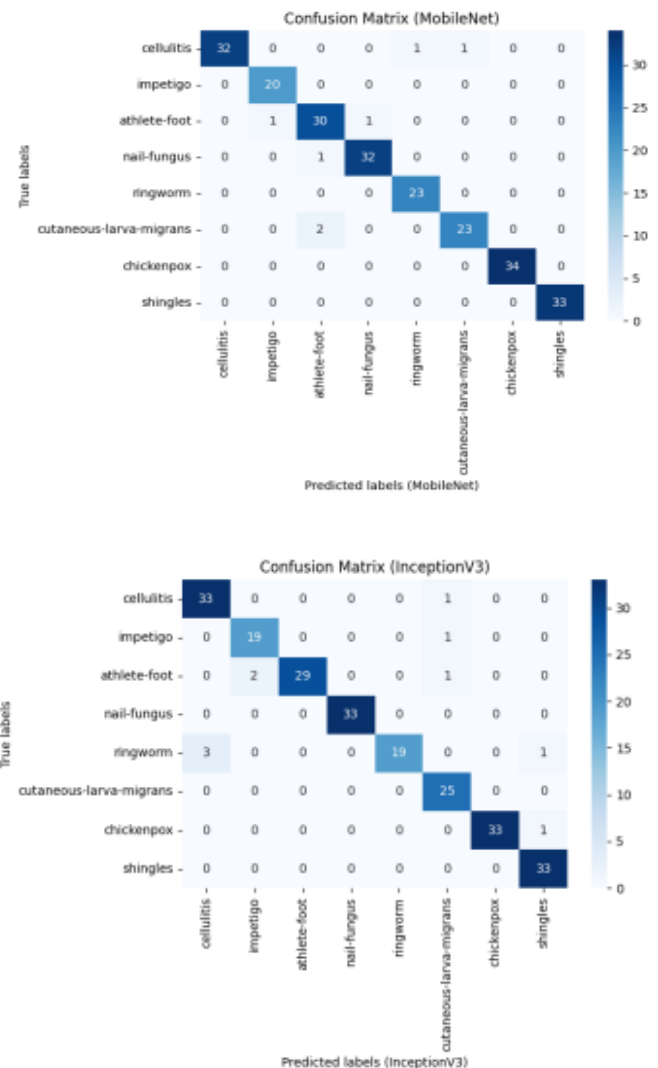
**C. Model Comparison:**

Both MobileNet and InceptionV3 showed exceptional overall accuracy in the test set. However, the accuracy of the MobileNet (97% compared to 96%) was somewhat higher than that of the InceptionV3. Despite some differences in certain classes, overall accuracy, recall, and F1 scores for each class were similar in both models.

Graphs and plots illustrating the training accuracy, training loss, and confusion matrices for both MobileNet and InceptionV3 are provided below in figure 2:



**Figure-3: Training Accuracy Comparison and Training Loss Comparison.**



**Figure-4: Confusion Matrix Comparison for MobileNet and InceptionV3.**

**D. Discussion:**

The results show that both MobileNet and InceptionV3 are effectively classified in the classification of skin diseases from images. Despite slight variations in performance, both models are highly accurate and show robustness in different disease classes. The choice of MobileNet and InceptionV3 depends on factors such as computational efficiency, model complexity, and specific application requirements.

**5.FUTURE SCOPE**

- 1. Dataset Expansion:** The models' ability for generalization can be improved by gathering larger and more varied datasets. To make the model more reliable and useful to a broader population, incorporate additional variations in skin conditions, demographics, and image characteristics

2. **Fine-tuning and Transfer Learning:** Use domain-specific data to investigate fine-tuning methods on previously learned models. This can assist in applying the knowledge gained from big datasets (such as ImageNet) to the unique features of photos of skin diseases.
  3. **Ensemble Methods:** Examine ensemble approaches, which aggregate predictions from several models to enhance performance as a whole. Ensemble methods can produce more accurate predictions and lessen the drawbacks of individual models.
  4. **Interpretability:** To comprehend the model, techniques like attention processes and class activation cards can be used. If clinics identify the features of the imaging that the model values highly, they can diagnose patients and schedule treatments more successfully.
  5. **Real-time Deployment:** Take into account that the model will be usable in real-time scenarios, such mobile apps and healthcare platforms. This results in a high degree of accuracy while lowering the model's size and processing demands.
  6. **Continued Evaluation:** Ongoing assessment based on fresh data to guarantee the model's long-term efficacy. It's critical to maintain the model current and relevant in case skin conditions change and new situations emerge.
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## 6. CONCLUSION

The study concludes that MobileNet and InceptionV3 models perform well in classifying skin diseases, as evidenced by their ability to correctly detect a range of skin ailments from pictures. Both models demonstrated robustness across several illness classifications and attained a high overall accuracy. Even though there were only slight performance variations, factors including computing efficiency, model complexity, and application needs may influence which of MobileNet and InceptionV3 is best.

Future developments in CNN-based skin disease detection appear promising. We can keep enhancing the precision, dependability, and application of these models in clinical practice and healthcare systems by growing datasets, improving model architectures, and investigating cutting-edge methods like ensemble learning and interpretability.

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