SKIN AI CARE: An Intelligent Dermatology

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Abstract- Skin-related disorders affect millions globally, making early and precise detection vital for effective treatment.This study proposes an AI-driven diagnostic tool employing deep learning, specifically utilizing the Mobile NetV2 architecture, for classifying eight types of common skin infections. These include bacterial, fungal, parasitic, and viral conditions. The model achieves a classification accuracy of 97%, making it apromising aid for dermatologists. Preprocessing steps like resizing, normalization, and label encoding were used to enhance model performance and ensure consistency. This work demonstrates how integrating AI in dermatology can streamline the diagnostic process and support clinical decision-making with improved accuracy.

Keywords: AI in Dermatology, MobileNetV2, Deep Learning, Skin Disease Detection,CNN, Image Classification.

1. INTRODUCTION

The human skin, being the body's largest organ, plays a fundamental role in safe guarding internal systems from external threats such as harmful microorganisms, environmental toxins, and ultraviolet (UV) radiation. Beyond this protective function, the skin also regulates body temperature, enables tactile sensation, and contributes significantly to personal identity and confidence. Despite its importance, the skin is frequently affected by a wide spectrum of diseases,many of which are becoming increasingly common due to environmental changes, lifestyle factors, and reduced healthcare awareness.

Globally, skin conditions range from benign disorders like acne to chronic illnesses such as eczema and even life-threatening diseases like melanoma. A significant number of these conditions are contagious and carry a substantial public health burden. Delays in early diagnosis and treatment whether due to unawareness, financial constraints, or neglect can lead to severe complications. This highlights the pressing need for greater awareness regarding skin health and for tools that facilitate early and accurate diagnosis.

According to the World Health Organization (WHO), nearly 900 million individuals worldwide suffer from skin conditions each year. In 2019 alone, there were approximately 4.86 billion new cases of skin and subcutaneous disorders globally. Of these, fungal infections accounted for 34% and bacterial infections for 23%. These conditions were also responsible for over 98,000 deaths and contributed significantly to the global burden of disease, with millions of disability-adjusted life years (DALYs) recorded (Yakupu et al., 2023) [1].As the field of medical science progresses, emerging technologies offer promising support in the realm of dermatology. However, many dermatological evaluations still rely on visual assessment by clinicians. Although effective in many scenarios, this traditional diagnostic method is limited by subjectivity, time constraints, and the potential for human error. The complexity and variability of skin presentations often result in differing opinions among professionals, making consistent diagnosis a challenge.

This is where artificial intelligence (AI) and machine learning (ML) present valuable opportunities. These technologies can enhance the diagnostic process by analyzing vast datasets to detect intricate patterns often overlooked by the human eye. Instead of replacing dermatologists, AI-based tools serve as decision support systems, helping clinicians achieve more consistent, accurate, and timely diagnoses.

By integrating AI models into clinical workflows, especially in resource-limited settings, healthcare providers can benefit from faster assessments and improved patient outcomes. The fusion of human expertise with computational precision holds great potential to transform the future of dermatological car offering a more reliable, scalable, and efficient approach to disease detection and management.

2. LITERATURESURVEY

Skin-related conditions are a major concern globally, impacting million so find ividuals across all age groups.Early and accurate diagnosis not only improves treatment outcomes for patients but also reduces the burden on healthcare infrastructures. With the rise of artificial intelligence(AI),particularly in the domain of deep learning, there has been a significant shift toward automated diagnostic systems that analyze medical images to detect and classify various skin conditions.

In recent years, deep learning models especially convolutional neural networks (CNNs) have become the backbone of image based medical diagnosis.Researchers have developed a range of modelsto assist dermatologists in making faster and more accurate decisions. These systems aim to mitigate delays associated with traditional methods such as biopsies or manual imagere views.This section review srecent advancements in the use of AI for skin disease detection. It includes a critical analysis of various methodologies, especially CNN-based models, and discusses challenges such as data diversity, variability in skin presentation, and the importance of large annotated datasets for model training. Additionally, it emphasizes the importance of ethical considerations and the integration of AI systems into real-world clinical environments. Kiand Rotstein (2009)

This study examined bacterial infections of the skin and soft tissues in adults. It focused on the factors that influence diagnosis and treatment including infection severity ,entry points ,and likely pathogens. The authors emphasized the importance of clinical knowledge for choosing the appropriate antimicrobial therapy to enhance patient recovery outcomes.

Sae-Limetal.(2020)

The authors introduced a skin lesion classification model based on a lightweight CNN architecture, MobileNet. Their optimized version of MobileNet demonstrated efficiency in classification tasks while maintaining low computational cost, making it suitable for mobile and embedded systems in dermatology.

Bandyopa dhyayetal.(2019)

A hybrid model integrating deep learning and classical machine learning was proposed. CNNs such as AlexNet, GoogleNet, ResNet50, and VGG16 were used for feature extraction, while algorithms like Support Vector Machines (SVM), Decision Trees, and AdaBoost were applied for classification. Their work offered a comparative study to determine the most effective model combinations for accurate disease prediction.

Maduranga and Nandasena(2019)

This research presented a mobile-based AI solution for classifying skin diseases using the HAM10000 dataset. Employing transfer learning with MobileNet, the model achieved 85% accuracy and was optimized for quick and reliable use in mobile healthcare applications. Shanthietal.(2020) A deep CNN consisting of 11 layers was designed to detect skin conditions such as eczema herpeticum, urticaria, keratosis, and acne. The model was trained on data from the Derm Net database and achieved high accuracy ranging from 98.6% to 99.04%, demonstrating its effectiveness in clinical image classification.

In all these works, the use of tools like Tens or Flow, Keras,and Open CV enabled the automation of keys tages including data preprocessing ,model development, training, and evaluation. These contributions demonstrate how AI and computer vision can be leveraged to improve the reliability and accessibility of skin disease diagnosis across various platforms, including real-time and mobile applications.

3. PROPOSED SYSTEM

This research presents an intelligent diagnostic system for identifying skin diseases using advanced deep learning strategies, supported by a well-structured data preprocessing framework. At the heart of this system is the MobileNetV2 model a highly efficient convolutional neural network known for its lightweight design and strong performance in image classification tasks.

The model is employed to extract critical features from dermatoscopic images, which are then used to categorize eight specific skin disease types. These include bacterial, fungal, parasitic, and viral conditions. To ensure the model performs consistently across a variety of datasets, arigorous preprocessing pipeline is implemented. This involves resizing all input images to a standard dimension and normalizing pixel values to reduce variability. These steps not only stream line the training process but also enhance the model's ability to generalize across diverse imaging conditions.

The system architecture, illustrated in Figure 1, integrates the full process from data collection and preparation to feature extraction and classification. This end-to-end frame work is designed to be scalable, efficient, and suitable for clinical deployment, particularly in environments where quick diagnosis is critical.

By utilizing a computationally efficient model like Mobile Net V2 and coupling it with clean, well processed data, the system delivers fast and reliable diagnostic results. It significantly reduces the time and effort required from medical professionals, thereby improving workflow efficiency and diagnostic precision.

Furthermore, the model is adaptable for telemedicine applications and remote healthcare services, especially in regions with limited access to dermatologists. In essence, this proposed solution highlight show the integration of modern AI techniques with structured data handling can revolutionize dermatological diagnostics enhancing both the accuracy of disease detection and the quality of patient care.

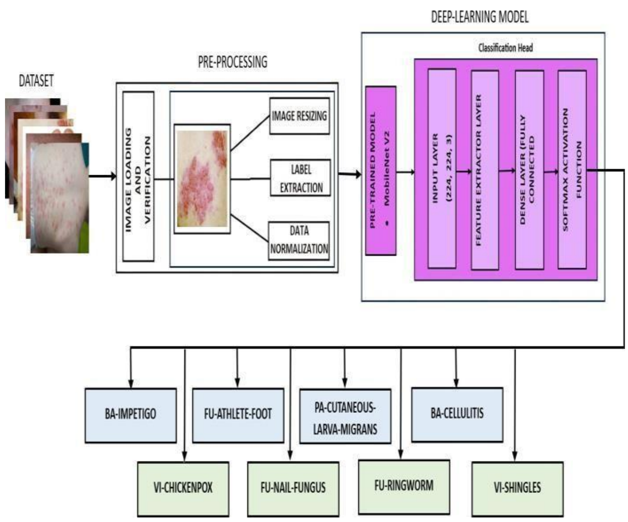

Figure.-1:Block Diagram of the Proposed Model

a. Deep Learning Model Construction

The architecture used for this system is based on a Convolutional NeuralNetwork(CNN), a type of deep learning model well-suited for image classification tasks. A standard CNN is composed of several key layers that work together to analyze image data and extract meaningful patterns.The following components outline the structure and function of each layer used in the model. Input Layer

This layer receives the raw image data. For instance, an image with dimensions 32x32 pixels and three color channels (Red, Green, Blue) is represented as an input tensor of size**[32×32×3]**.This layer simply holds the pixel values and passes them to the next layer for processing.

i. Convolutional Layer

The convolutional layer applies multiple filters (also known as kernels) across the image to extract local patterns such as edges or textures. Each filter performs a dot product with a small portion of the input image. For example,using12 filters would produce an output volume of[32×32×12], where each channel corresponds to one filter.

ii.ReLU(Rectified Linear Unit) Layer

This activation layer introduces non-linearity into the model by applying a function like ReLU = max(0, x) to each element. This helps the network learn complex patterns by discarding negative values while keeping the size of the feature map unchanged (e.g., still[32×32×12]).

iii.Pooling Layer

Also known as the subsampling or down sampling layer, it reduces the spatial dimensions of the feature map to decrease Computational load and prevent overfitting. A common approach is max pooling, which might reduce the feature map to [16×16×12]by selecting the maximum value from each 2×2 region.

iv. Fully Connected or Dense Layer

After several convolution and pooling operations, the resulting feature maps are flattened into a one-dimensional vector.This vectoris then fed into one or more dense layers that compute the final classification scores. Each output neuron represents a different skin disease class. The final layer typically uses a Soft Max activation to output a probability distribution across all possible classes. This hierarchical structure allows the CNN to progressively learning creasingly abstract features from the raw image data, leading to more accurate and robust classification of skin diseases

b. Dataset and Dataset Handling (Plagiarism-Free)

Skin infections can arise when naturally occurring microorganisms on the skin such as bacteria and fungi proliferate beyond normal levels, overpowering the body's immune defense. The type of microorganism involved typically determines the nature and severity of the skin disease.

For this study, the dataset was obtained from Kaggle, a popular data science platform. It consists of labeled dermatological images categorized into eight distinct types of skin infections. The dataset is neatly organized, with each class stored in a separate folder, making it easy to associate each image with its corresponding label during the training process.

The infections represented in the dataset cover abroad range of microbial origins:

Bacterial Infections: Cellulitis, Impetigo
Fungal Infections: Athlete's Foot **,**Nail Fungus Ringworm
Parasitic Infections: Cutaneous Larva Migrans
Viral Infections: Chickenpox Shingles

This folder-based hierarchy simplifies data set management and supports efficient preprocessing and training workflows. The structured format ensures that images are easily accessible and grouped by infection type, allowing the deep learning model to learn clear distinctions between categories. Overall, the dataset's diversity covering multiple types of pathogens makes it well-suited for training a robust skin disease classification model that can generalize effectively across various infection types.

c. Data Preprocessing (Plagiarism-Free)

To ensure the deep learning model receives clean, uniform, and structured data, several preprocessing steps are performed prior to training:

i. **Image Loading and Validation**

Images are loaded from the dataset directories into memory. As part of quality control, each image is checked to ensure it is readable and uncorrupted. Faulty or incomplete files are discarded to maintain data consistency and integrity.

ii. **Image Resizing**

All images are resized to a standard dimension of 224×224 pixels, which is a common input size form any CNN architectures including MobileNetV2. This step ensures that all inputs are of uniform size, facilitating batch processing and model compatibility.

iii. **Label Assignment**

The directory structure, where each subfolder represents a disease class, is used to assign numerical labels to the images. This automated labeling process allows each image to be correctly mapped to its respective infection category.

iv. **Pixel Normalization**

The pixel values of all images are scaled to a range of 0 to 1 by dividing by 255. This normalization step helps balance the feature scales, ensuring that no pixel intensity disproportionately influences the model during training.

d. Deep Learning Model Construction

The core classification engine is built using MobileNetV2, a lightweight yet powerful pre-trained convolutional neural

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network model.

i. **TransferLearningwithMobileNetV2**

MobileNetV2 is employed as a feature extractor. This model, pre-trained on a large-scale image dataset (like Image Net), brings robust generalization capabilities, especially useful for medical image analysis with limited data.

ii. **Input Layer**

The network begins with an input layer configured to accept images of size 224×224×3(height, width, RGB channels).This ensures compatibility with Mobile NetV2'sinputrequirements.

iii. **Feature Extraction Layer**

The MobileNetV2 base model is integrated into the network to extract high-level features from the input images.These features represent essential patterns and textures relevant to distinguishing between various skin diseases.

iv. **Output Layer**

A final SoftMax layer is added with eight output neurons, each representing a skin disease class. The SoftMax function converts the model's output into a probability distribution across the classes, enabling multiclass prediction.

e. Model Training(Plagiarism-Free)

The model training phase involves configuring the learning process and optimizing performance on the dataset.

i. **Model Compilation**

The model is compiled using Sparse Categorical Cross-Entropy as the loss function, which is appropriate for multi-

Figure-2:Classification Report for Mobile Net and InceptionV3

MobileNet Classification Report:

	precision	recall	f1-score	support
0	1.00	0.94	0.97	34
1	0.95	1.00	0.98	20
2	0.91	0.94	0.92	32
3	0.97	0.97	0.97	33
4	0.96	1.00	0.98	23
5	0.96	0.92	0.94	25
6	1.00	1.00	1.00	34
7	1.00	1.00	1.00	33
accuracy			0.97	234
macro avg	0.97	0.97	0.97	234
weighted avg	0.97	0.97	0.97	234

InceptionV3 Classification Report:

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

class classification problems with integer labels. The **Adam optimizer** is chosen for its adaptive learning rate and efficient convergence properties.

ii. **Training Process**

The model is trained iteratively over multiple epochs using the preprocessed images. During each epoch, the model updates its internal parameters by minimizing the loss function. This optimization continues until performance stabilizes, indicating that the model has effectively learned to classify skin conditions.

4. PERFORMANCEANALYSIS

a. Experimental Setup:

To evaluate the effectiveness of the proposed system, experiments were conducted using two well-known deep learning architectures: Mobile Net V2 and InceptionV3. Both models were trained and tested on adatasetconsistingof1,159labeled images spanning eight skin disease categories: *cellulitis*, *impetigo*, *athlete's foot*, *nail fungus*, *ringworm*, *cutaneous larva migrans*, *chickenpox*, and *shingles*.

Before training, all images were preprocessed to match the input specifications required by each model, including resizing and normalization. The models were then trained using a stratified training set and evaluated on a separate test set to ensure reliable performance measurement.

The assessment was carried out using standard evaluation metrics commonly applied in multi-class classification tasks:

Accuracy–Overall correctness of the model's predictions.

Loss–A measure of prediction error during training.

Precision–The proportion of correctly predicted positive cases.

Recall – The ability of the model to detect all relevant instances.

F1-Score – The harmonic mean of precision and recall, offering a balanced measure.

b. Model Evaluation:

BothMobileNetV2andInceptionV3wereassessedusing a reserved portion of the dataset (test set) that was not used during training. The evaluation focused on comparing their classification performance across the eight skin disease categories.

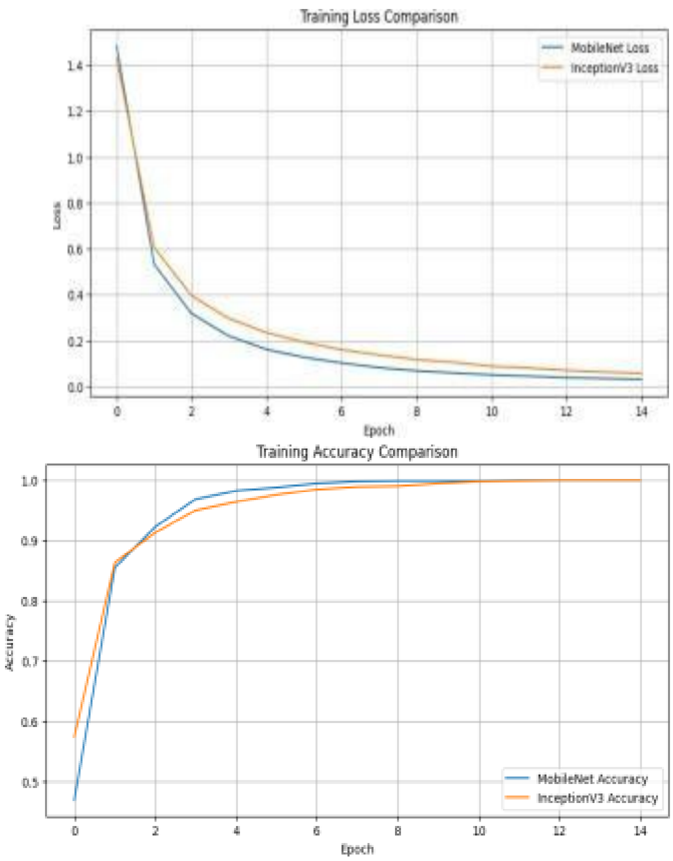
The results, summarized in Figure 2, include detailed classification reports that present the per-class precision, recall, and F1-score for each model. These reports provide insights into how well each architecture performed in identifying different types of skin infections. While both models achieved high accuracy, MobileNetV2 demonstrated slightly better overall performance, offering a more lightweight and efficient solution suitable for real-time applications.

c. *Model Comparison*:

Both MobileNetV2 and InceptionV3 demonstrated strong performance on the classification task when teste don unseen data.While both models achieved high accuracy, MobileNetV2 slightly outperformed InceptionV3, achieving a classification accuracy of 97%, compared to 96% for InceptionV3.

Although the two models performed similarly across most evaluation metrics such as precision, recall, and F1-score MobileNetV2's marginal advantage, along with its faster computation and lower memory footprint, makes it more suitable for lightweight applications, including mobile-based diagnostics.

Detailed visualizations such as training accuracy and loss curves, along with confusion matrices for each model, are presented in Figure 2. These graphical representations offer further insight into the models' learning behavior and classification consistency across the eight skin disease categories.



d. *Discussion:*

The evaluation results indicate that both MobileNetV2 and InceptionV3 are highly effective in classifying various types of skin diseases from medical images. Each model demonstrated strong generalization capabilities and delivered reliable predictions across all eight disease categories.

While MobileNetV2 held a slight edge in overall accuracy, both models were consistent in their performance across key metrics such as precision, recall, and F1-score. The final choice between these two architectures should be guided by the specific use case. For instance, MobileNetV2 is ideal for applications where speed and computational efficiency are critical such as in mobile or edge devices while InceptionV3 might be preferred in environments where slightly higher complexity is acceptable in exchange for additional flexibility in feature learning.

Overall, the findings validate the potential of deep learning models in enhancing diagnostic accuracy and providing scalable solutions for automated dermatological assessments.

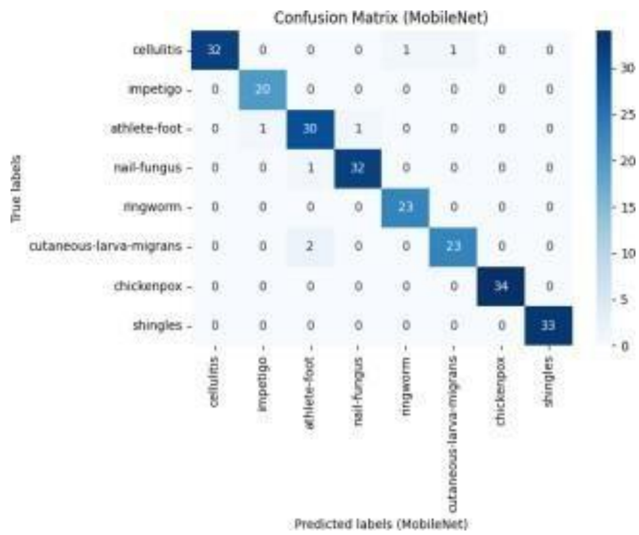


Figure-3:Training Accuracy Comparison and Training LossComparison.

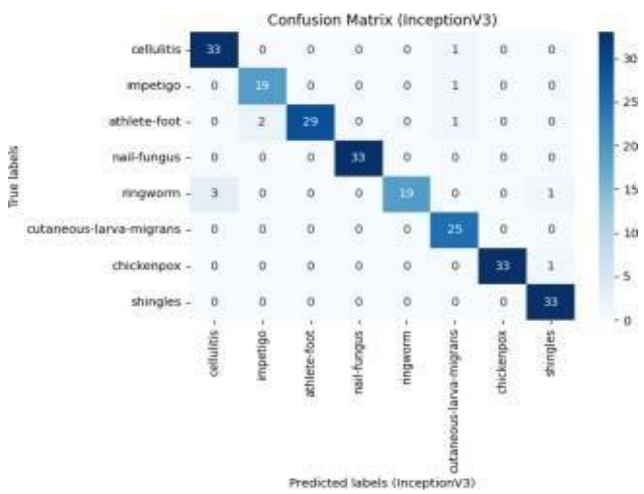


Figure-4:Confusion Matrix Comparison for Mobile Net and InceptionV3.

CONCLUSION

This study demonstrates that both Mobile Net and InceptionV3 models are effective for classifying skin diseases, showing strong capabilities in accurately identifying various skin conditions from images. Both models exhibited consistent robustness across multiple disease categories and achieved high over all accuracy. Although their performance differences were marginal, factors such as computational efficiency, model complexity, and specific application requirements should be considered when choosing between Mobile Net and InceptionV3.

The future of CNN based skin disease detection holds great potential. Continued improvements in dataset size, model design, and exploration of advanced techniques such as ensemble learning and model interpretability will further enhance the accuracy, reliability, and clinical applicability of these systems in healthcare settings.

REFERENCES

1. Yakupu,R.Aimaier,B.Yuan,B.Chen,J.Cheng,Y.Zhao, Y. Peng, J. Dong, and S. Lu, “The burden of skin and subcutaneous diseases: Findings from the Global Burden of Disease Study 2019,” Frontiers in Public Health, vol. 11, p. 1145513, Apr. 2023, doi: 10.3389/fpubh.2023.1145513.

2. V. Ki and C. Rotstein, “Bacterial skin and soft tissue infections in adults: A review of their epidemiology, pathogenesis, diagnosis, treatment and site of care,” Canadian Journal of Infectious Diseases and Medical Microbiology, vol. 20, no. 2, pp. 52–56, 2009, doi: 10.1155/2009/423868.

3. W. Sae-Lim, W. Wettayaprasit, and P. Aiyarak, “Convolutional Neural Networks using MobileNet for skin lesion classification,” in Proc. 12th Int. Conf. on Information Technology and Electrical Engineering (ICITEE),ChiangMai,Thailand,2020,pp.132–137,doi: 10.1109/ICITEE49829.2020.9271682.

4. S. K. Bandyopadhyay, P. Bose, A. Bhaumik, and S. Poddar, “Machine learning and deep learning integration for skin diseases prediction,” International Journal of Computer Science and Mobile Computing, vol. 8, no. 5, pp. 88–93, May 2019.

5. M. W. P. Maduranga and D. Nandasena, “Mobile-based skin disease diagnosis system using convolutional neuralnetworks (CNN),”inProc.Int.ResearchConf.on Smart Computing and Systems Engineering (SCSE), Sri Lanka, 2019, pp. 50–55.

6. T. Shanthi, R. S. Sabeenian, and R. Anand, “Automatic diagnosis of skin diseases using convolution neural network,” Materials Today: Proceedings, vol. 33, no. 8,