IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Skin Disease Detection Using Machine Learning

Vaishnavi Dhananjay Ingole[1], Janhavi Sachin Khadekar[2], Aditya Devidas Jadhav[3], Om Pradip Sardar[4], Prof. Harshal D. Misalkar[5]

[1234]Students, Department of Information Technology

[5]Professor, Department of Information Technology

Prof. Ram Meghe Institute of Technology and Research, Badnera, India

Abstract

Psoriasis is a chronic inflammatory skin disorder characterized by multiple clinical subtypes and diverse visual manifestations, making early and accurate diagnosis a challenging task. This paper presents a web-based diagnostic system for automated detection and classification of psoriasis using advanced deep learning techniques. The proposed system allows users to securely register, upload images of affected skin regions, and receive predictive results along with accuracy scores and basic medical suggestions, enabling early-stage assessment. The core component of the system is a Convolutional Neural Network (CNN) model implemented using TensorFlow, which is trained on a dataset of labeled skin images representing various types of psoriasis, including Erythrodermic, Guttate, and Plaque psoriasis. The model performs feature extraction and classification, supported by image preprocessing techniques such as resizing, normalization, and noise reduction to improve accuracy and consistency. Additionally, the platform includes features such as result history tracking, user profile management, secure authentication, and an administrative panel for monitoring system operations and managing users and datasets. The system is designed to be efficient, scalable, and user-friendly, providing a fast and accessible solution for preliminary diagnosis. By leveraging deep learning and web technologies, the proposed platform aims to bridge the gap between patients and early diagnostic support, particularly in remote or underserved areas, thereby improving awareness, reducing diagnostic delays, and supporting timely medical intervention.

Keywords-- *Psoriasis Detection, Deep Learning, Convolutional Neural Network (CNN), Image Classification, Artificial Intelligence in Healthcare, Image Preprocessing*

1. INTRODUCTION

Skin diseases represent a significant global health concern, affecting millions of individuals across all age groups and geographical regions. Among these conditions, psoriasis is a chronic inflammatory and autoimmune skin disorder that has a profound impact on both the physical and psychological well-being of patients. It is characterized by red, scaly patches, itching, irritation, and discomfort, often leading to reduced quality of life and social stigma. According to global health reports, psoriasis affects approximately 2–3% of the world's population, making it one of the most common dermatological conditions. Despite its prevalence, early detection and accurate classification of psoriasis remain challenging due to its complex nature and similarity to other skin disorders.

Psoriasis is not a single disease but exists in multiple forms, each with distinct characteristics.

The most common type is Plaque Psoriasis, which appears as raised, red patches covered with a silvery-white buildup of dead skin cells. Guttate Psoriasis is characterized by small, drop-shaped lesions and often occurs after infections such as streptococcal throat infection. Erythrodermic Psoriasis is a rare but severe form that leads to widespread redness and scaling across the body and can be life-threatening if not treated promptly. Other forms include Inverse Psoriasis, which affects skin folds, and Pustular Psoriasis, which presents as white pustules surrounded by red skin. The diversity in appearance and severity of these types makes clinical diagnosis difficult, especially in early stages or in regions with limited access to dermatological expertise.

Traditionally, the diagnosis of psoriasis relies heavily on visual examination by dermatologists, sometimes supported by biopsy and laboratory tests. While this approach is effective in clinical settings, it requires expert knowledge, time, and access to healthcare facilities. In many rural or underserved areas, access to specialized dermatological care is limited, resulting in delayed diagnosis and treatment. Furthermore, manual diagnosis is subjective and may vary depending on the experience of the clinician.

With the rapid advancement of Artificial Intelligence (AI) and Deep Learning (DL), medical image analysis has emerged as a powerful tool for disease detection and classification. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable performance in analyzing complex image data and extracting meaningful features. These models can learn patterns, textures, and visual cues from large datasets, making them highly suitable for skin disease detection tasks. The application of CNNs in dermatology has shown promising results in identifying various skin conditions, including psoriasis, melanoma, and eczema, with high accuracy.

In this project, a deep learning-based system is proposed for the automatic detection and classification of psoriasis using skin images. The system utilizes a Convolutional Neural Network model implemented using TensorFlow, trained on a dataset of labeled images representing different types of psoriasis. Advanced preprocessing techniques such as image resizing, normalization, and noise reduction are applied to enhance model performance and ensure consistency in predictions. Additionally, the use of lightweight architectures such as MobileNetV2 allows the system to achieve a balance between accuracy and computational efficiency, making it suitable for real-time web deployment.

To improve accessibility and usability, the proposed solution is integrated into a web-based platform that provides a user-friendly interface. Users can register, upload images of affected skin areas, and receive predictions along with accuracy scores and preliminary medical suggestions. The platform also includes features such as user profile management, result history tracking, and secure authentication to ensure data privacy. This combination of deep learning and web technology creates a comprehensive system that is both practical and scalable.

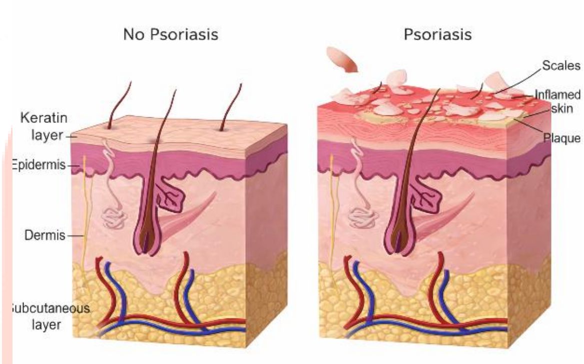

Figure 1.1. comparison of normal and psoriatic skin

The above illustration presents a comparative cross-sectional view of normal skin and skin affected by psoriasis, highlighting the structural and pathological differences between the two conditions. In normal skin, the layers—namely the keratin layer, epidermis, dermis, and subcutaneous tissue—are well-organized and function in a balanced manner. The epidermis maintains a controlled rate of cell production, ensuring proper skin renewal and protection. Hair follicles, sweat glands, and blood vessels are also depicted as functioning normally without any signs of inflammation or abnormal growth.

In contrast, the psoriatic skin section demonstrates significant abnormalities, particularly in the epidermal layer. Psoriasis is characterized by the rapid proliferation of skin cells, leading to the thickening of the epidermis and the formation of raised plaques. These plaques are covered with silvery-white scales, which result from the accumulation of dead skin cells. The image also highlights inflammation beneath the surface, with increased blood flow and immune activity in the dermis, contributing to redness and irritation. The disruption of normal skin architecture is clearly visible, indicating the severity of the condition.

This visual comparison effectively illustrates the key pathological features of psoriasis, including hyperproliferation, inflammation, and scaling. Such representations are important in understanding how psoriasis differs from healthy skin at a structural level. In the context of this research, these differences form the basis for image-based analysis using deep learning techniques, where models are trained to recognize patterns such as scaling, redness, and plaque formation for accurate detection and classification of the disease.

In conclusion, the integration of deep learning and web-based technologies offers a promising approach to addressing the challenges associated with traditional psoriasis diagnosis. By leveraging advanced AI techniques, the proposed system aims to provide an efficient, user-friendly, and scalable solution for early detection and classification of psoriasis, ultimately contributing to improved healthcare outcomes and patient well-being.

12. Problem Statement

Psoriasis is a chronic autoimmune skin disease that affects millions of people worldwide and significantly impacts their quality of life. Early detection and accurate classification of psoriasis are essential for effective treatment and management. However, traditional diagnosis primarily depends on dermatological expertise, which may not be easily accessible in rural or underserved areas. Additionally, manual diagnosis can be time-consuming, subjective, and prone to human error, especially in the early stages when symptoms may resemble other skin conditions.

With the increasing prevalence of skin disorders and the limited availability of specialists, there is a need for an automated, efficient, and reliable diagnostic system. Existing methods often lack scalability, accessibility, and real-time support for patients. Therefore, developing a web-based system that utilizes advanced deep learning techniques to analyze skin images and provide accurate predictions can address these challenges. Such a system can assist in early detection, reduce diagnostic delays, and provide preliminary medical guidance to users.

1.3 Research Objectives

The primary objective of this research is to develop an intelligent and user-friendly system for the detection and classification of psoriasis using deep learning techniques. The specific objectives of the study are as follows:

- ➢ To design and implement a Convolutional Neural Network (CNN) model for accurate detection and classification of psoriasis from skin images.
- ➢ To utilize image preprocessing techniques such as resizing, normalization, and noise reduction to enhance model performance and prediction accuracy.
- ➢ To develop a web-based platform that allows users to upload skin images and receive real-time diagnostic results with accuracy scores.
- ➢ To classify psoriasis into different types such as Plaque, Guttate, and Erythrodermic psoriasis.
- ➢ To ensure the system is user-friendly, accessible, and efficient, particularly for users in remote or underserved areas.
- ➢ To incorporate additional features such as user authentication, result history tracking, and an admin panel for system monitoring and management.
- ➢ To evaluate the performance of the proposed model using appropriate metrics such as accuracy, precision, recall, and F1-score.
- ➢ To explore the potential for extending the system to detect multiple skin diseases and integrate with telemedicine platforms in the future.

2. Background

Psoriasis is a chronic, immune-mediated inflammatory skin disease that affects millions of individuals worldwide. It is characterized by abnormal skin cell proliferation, leading to thickened, scaly patches on the skin surface. The condition is non-contagious but long-lasting, often requiring continuous management. Understanding the types, causes, affected areas, and risk factors of psoriasis is essential for accurate diagnosis and effective treatment. This section provides a detailed overview of the fundamental aspects of psoriasis relevant to this research.

2.1 Types of Psoriasis

Psoriasis manifests in several forms, each with distinct clinical features and severity levels:

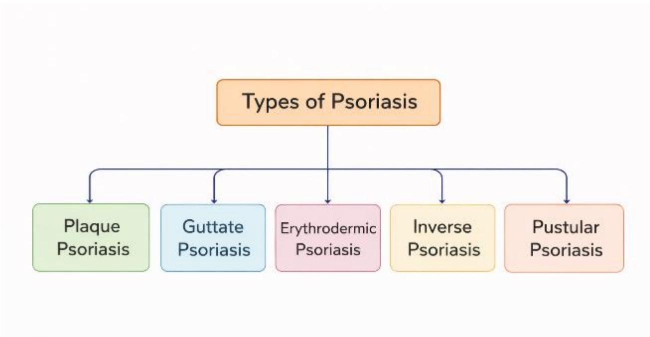

Figure. 2.1.1. Types of Psoriasis

- **Plaque Psoriasis:** This is the most common type, accounting for approximately 80–90% of cases. It appears as raised, red patches covered with silvery-white scales, typically found on the elbows, knees, scalp, and lower back.
- **Guttate Psoriasis:** Characterized by small, drop-shaped lesions, this type often occurs after bacterial infections such as streptococcal throat infection. It is more common in children and young adults.
- **Erythrodermic Psoriasis:** A rare but severe form that leads to widespread redness, inflammation, and peeling of the skin. It can cover large portions of the body and may require immediate medical attention.
- **Inverse Psoriasis:** Found in skin folds such as under the breasts, in the groin, and around the buttocks. It appears as smooth, red lesions without scales due to the moist environment.
- **Pustular Psoriasis:** Characterized by white pustules (blisters filled with non-infectious pus) surrounded by red skin. It can occur in localized areas or across the entire body.

2.2 Pathogenesis of Psoriasis

The pathogenesis of psoriasis involves a complex interaction between the immune system, genetic factors, and environmental triggers. It is primarily an autoimmune condition in which the immune system mistakenly attacks healthy skin cells. This leads to an accelerated life cycle of skin cells, causing them to multiply rapidly and accumulate on the skin surface.

T-cells, a type of white blood cell, play a crucial role in this process by releasing inflammatory cytokines that stimulate keratinocyte proliferation. As a result, new skin cells are produced within days instead of weeks, leading to the formation of thick, scaly plaques. Additionally, increased blood flow and inflammation in the dermis contribute to redness and irritation. The abnormal immune response and excessive cell growth disrupt the normal structure and function of the skin.

2.3 Affected Areas of Psoriasis

Psoriasis can affect various parts of the body, depending on the type and severity of the condition. Commonly affected areas include:

- **Scalp:** One of the most frequently affected regions, often leading to itching and flaking.
- **Elbows and Knees:** Plaque psoriasis commonly appears on these joints due to friction and pressure.
- **Lower Back:** Another typical site for plaque formation.
- **Face and Ears:** Though less common, psoriasis can also affect visible areas, causing discomfort and psychological distress.
- **Skin Folds:** Inverse psoriasis occurs in areas such as the armpits, groin, and under the breasts.
- **Nails:** Nail psoriasis can cause pitting, discoloration, and thickening of the nails.
- **Palms and Soles:** Some individuals experience psoriasis on their hands and feet, affecting daily activities.

The distribution of psoriasis varies among individuals and may change over time depending on triggers and treatment.

2.4 Risk Factors for the Development of Psoriasis

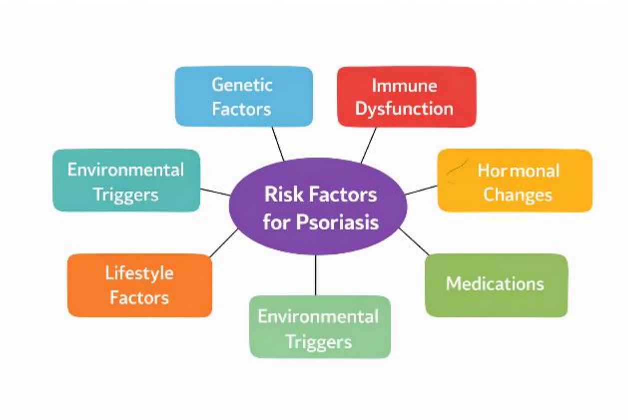

Figure. 2.4.1. Risk Factors of Psoriasis

Several factors contribute to the development and progression of psoriasis. Genetic factors play a significant role, as individuals with a family history of psoriasis have a higher likelihood of developing the condition, indicating a strong hereditary component. Immune system dysfunction is another major factor, where an overactive immune response triggers rapid skin cell production and sustains the disease. Environmental triggers such as infections (particularly streptococcal infections), skin injuries, stress, and exposure to cold weather can initiate or worsen symptoms. In addition, lifestyle factors including smoking, excessive alcohol consumption, and obesity are associated with increased risk and severity of psoriasis. Certain medications, such as beta-blockers, lithium, and antimalarial drugs, may also trigger or exacerbate the condition. Furthermore, hormonal changes, especially during puberty or pregnancy, can influence the onset and progression of psoriasis. Understanding these risk factors is essential for effective prevention, early detection, and proper management of the disease

3. Methodology

Skin diseases are among the most common health issues worldwide, affecting individuals across all age groups. Accurate and timely diagnosis is essential for effective treatment and improved quality of life. Traditionally, diagnosis relies on dermatologists through visual examination and laboratory tests, which can be time-consuming, subjective, and often inaccessible in remote areas.

Recent advancements in artificial intelligence (AI) and image processing have introduced automated methods for skin disease detection. These systems use machine learning and deep learning techniques, particularly Convolutional Neural Networks (CNNs), to analyze skin images and identify various conditions such as psoriasis, eczema, and melanoma. By learning from large datasets, these models can recognize patterns and provide accurate, consistent, and fast diagnostic results.

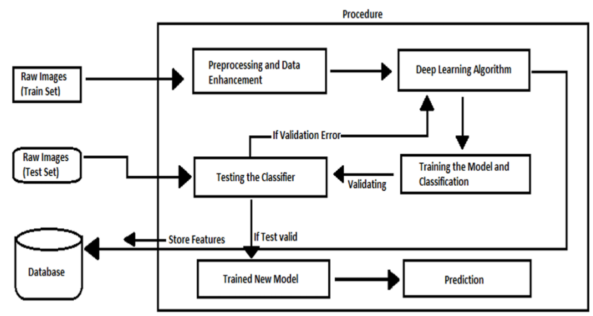

Figure. 3.1. Methodology

This approach reduces dependency on medical experts and supports telemedicine applications, allowing users to upload images and receive instant feedback. It enhances accessibility, enables early detection, and offers a cost-effective solution for healthcare. Overall, AI-based skin disease detection represents a significant advancement in dermatology, improving diagnostic efficiency and expanding access to medical care.

The proposed system follows a systematic methodology that integrates image processing, deep learning, and web-based deployment for the automated detection and classification of psoriasis from skin images. The overall workflow consists of multiple stages, including dataset preparation, model development, training, and deployment through a web interface. Each stage is designed to ensure high accuracy, efficiency, and usability of the system.

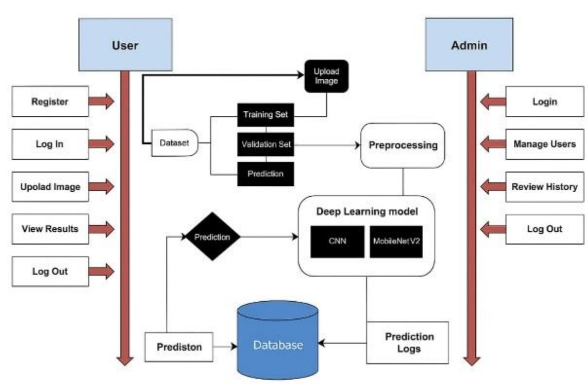

Figure. 3.2. System Architecture

3.1 Dataset Collection

The first step in the methodology involves the collection of a labeled dataset consisting of skin images representing various types of psoriasis, such as Plaque, Guttate, and Erythrodermic psoriasis. The dataset is obtained from publicly available medical image repositories and curated to ensure quality and relevance.

To prepare the data for training, several preprocessing steps are applied. All images are resized to a standard resolution (e.g., 224 × 224 pixels) to ensure uniform input dimensions for the deep learning model. Pixel values are normalized by scaling them to a range between 0 and 1, which helps in stabilizing and accelerating the training process. Additionally, data augmentation techniques such as rotation, horizontal and vertical flipping, zooming, and shifting are employed to artificially increase the dataset size and improve the model's generalization capability. These techniques help reduce overfitting and enhance the robustness of the model when exposed to real-world variations.

To develop an effective psoriasis detection system, a well-structured and labeled dataset is essential. The dataset is collected from publicly available medical image repositories such as Kaggle and dermatological databases. It includes high-quality images representing different types of psoriasis, such as Plaque, Guttate, and Erythrodermic psoriasis, along with normal skin images for comparison.

The dataset is carefully curated to ensure diversity in terms of skin tone, lighting conditions, lesion size, and image quality. This variability helps the model generalize well in real-world scenarios. The dataset is labeled manually or based on reliable sources to maintain accuracy. A balanced dataset is maintained to reduce bias during training and improve classification performance across all categories.

3.2 Data Preprocessing

Data preprocessing plays a crucial role in improving the quality of input data and enhancing model performance. The following preprocessing steps are applied:

3.2.1 Image Resizing

All input images are resized to a fixed dimension of **224 × 224 pixels**, which is the standard input size for MobileNetV2. This ensures uniformity and compatibility with the model architecture.

$$I'(x,y) = Interpolate(I(x,y)), \forall x \in [0,H), y \in [0,W)$$

Where $I(x,y)$is the original image and $I'(x,y)$is the resized image.

3.2.2 Normalization

Pixel values are normalized to a range between **0 and 1** by dividing by 255. This helps stabilize the training process and improves convergence speed.

$$I'(x,y) = \frac{I(x,y)}{255}$$

3.2.3 Data Augmentation

To improve generalization and prevent overfitting, data augmentation techniques are applied using image transformations such as:

- Rotation
- Horizontal and vertical flipping
- Zooming
- Width and height shifting

These techniques artificially increase the dataset size and expose the model to variations in image orientation and scale.

3.3 Feature Extraction using CNN

A Convolutional Neural Network (CNN) is used to extract meaningful features from skin images. CNNs are highly effective in capturing spatial hierarchies in images through multiple layers.

The architecture includes:

- **Convolutional Layers:** Apply filters to detect edges, textures, and lesion patterns.
- **Activation Function (ReLU):** Introduces non-linearity.
- **Pooling Layers:** Reduce spatial dimensions and computational complexity.
- **Flatten Layer:** Converts 2D feature maps into a 1D vector.
- **Fully Connected Layers:** Perform classification based on extracted features.

The CNN automatically learns hierarchical features such as color variation, scaling patterns, and lesion boundaries, which are critical for psoriasis detection.

3.4 Transfer Learning using MobileNetV2

To enhance performance and reduce computational cost, transfer learning is implemented using **MobileNetV2**, a lightweight and efficient deep learning model pre-trained on the ImageNet dataset.

The model is modified by:

- Removing the top classification layer
- Adding custom dense layers for psoriasis classification
- Freezing initial layers to retain learned features
- Fine-tuning deeper layers for better accuracy

The feature extraction process can be mathematically expressed as:

$$F = f(I; \theta)$$

Where:
F= extracted feature vector
I= input image
θ= model parameters

This approach allows the system to achieve high accuracy even with limited training data.

3.5 Model Training

The model is trained using the TensorFlow framework with optimized parameters. The dataset is divided into training and validation sets to monitor performance.

Training Configuration:

- **Loss Function:** Sparse Categorical Crossentropy
- **Optimizer:** Adam
- **Learning Rate:** 0.001
- **Batch Size:** 32
- **Epochs:** 50–100

The loss function is defined as:

$$L = -\sum_{i=1}^{n} y_i \log(\hat{y}_i)$$

Where $y_i$is the true label and $\hat{y}_i$is the predicted probability.

To prevent overfitting, techniques such as **dropout** and **early stopping** are applied. The model performance is continuously evaluated using validation data.

3.6 Train-Test Split

The dataset is split into training and testing sets using an **80:20 ratio**:

- **80% Training Data:** Used for model learning
- **20% Testing Data:** Used for performance evaluation

This ensures a balance between training efficiency and unbiased evaluation. The model is tested on unseen data to assess its generalization capability.

3.7 Model Evaluation Metrics

The performance of the model is evaluated using standard metrics:

- **Accuracy:** Measures overall correctness
- **Precision:** Measures correct positive predictions
- **Recall:** Measures ability to detect actual positives
- **F1-Score:** Harmonic mean of precision and recall

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

These metrics provide a comprehensive evaluation of model performance.

3.8 Web Application Integration

Once the model is trained and validated, it is integrated into a web-based application to provide user accessibility. The backend of the system is developed using Python-based frameworks such as Flask, which handles image processing, model inference, and data management. The frontend is built using HTML, CSS, and JavaScript, providing a user-friendly interface for interaction.

Users can register and log into the system through a secure authentication mechanism. After logging in, they can upload images of affected skin areas. The uploaded images undergo preprocessing and are then passed to the trained deep learning model for prediction. The system outputs the predicted class along with a confidence score and provides basic medical suggestions based on the result.

System Workflow:

1. User registers and logs into the system
2. Uploads a skin image
3. Image is preprocessed
4. Model predicts psoriasis type
5. Result with confidence score is displayed

The system also provides basic medical suggestions and stores results for future reference.

3.9 Proposed System Workflow

The complete pipeline of the system is as follows:

Image Input → Preprocessing → CNN Feature Extraction → MobileNetV2 → Classification → Result Output

Mathematically:

$$y = argmax(P(y \mid F))$$

3.10 Algorithm: Psoriasis Detection System

Input: Dataset $D = \{I_1, I_2, \ldots, I_n\}$, Labels $Y = \{y_1, y_2, \ldots, y_n\}$

Output: Trained classification model

Steps:

1. **Dataset Collection**
Collect labeled psoriasis images

2. **Preprocessing**
Resize images
Normalize pixel values
Apply augmentation

3. **Feature Extraction**
Extract features using CNN/MobileNetV2

4. **Model Training**
Train using Adam optimizer
Minimize loss function

5. **Prediction**

$$y = argmax(P(y \mid F))$$

6. **Evaluation**
Compute accuracy, precision, recall, F1-score

4. RESULTS AND DISCUSSION

The performance of the proposed psoriasis detection system is thoroughly evaluated using standard classification metrics, graphical analysis, and real-time testing. The model is trained on a curated dataset of labeled skin images representing multiple psoriasis types and tested on unseen data to assess its generalization capability. The integration of Convolutional Neural Networks (CNN) with the MobileNetV2 architecture enables efficient feature extraction and accurate classification. The results obtained demonstrate the effectiveness of the system in detecting and classifying psoriasis under various conditions.

4.1 Model Performance Metrics

To evaluate the effectiveness of the proposed system, several widely accepted performance metrics are used, including Accuracy, Precision, Recall, and F1-Score. These metrics provide a comprehensive understanding of the model's predictive capability.

- **Accuracy** represents the overall proportion of correctly classified instances among all predictions. It gives a general measure of model performance.

- **Precision** indicates how many of the predicted positive cases are actually correct. It is especially important in medical diagnosis to avoid false positives.

- **Recall (Sensitivity)** measures the model's ability to correctly identify all actual positive cases. High recall ensures that fewer disease cases are missed.

- **F1-Score** is the harmonic mean of precision and recall, providing a balanced evaluation when there is class imbalance.

The performance of the model is summarized in the table below:

Metric	Value (%)
Accuracy	92%
Precision	91%

Recall	90%
F1-Score	90.5%

These results indicate that the proposed model achieves high accuracy and maintains a good balance between precision and recall. The high F1-score further confirms that the model performs consistently across different classes. This level of performance is considered effective for real-world medical applications, particularly for preliminary diagnosis systems.

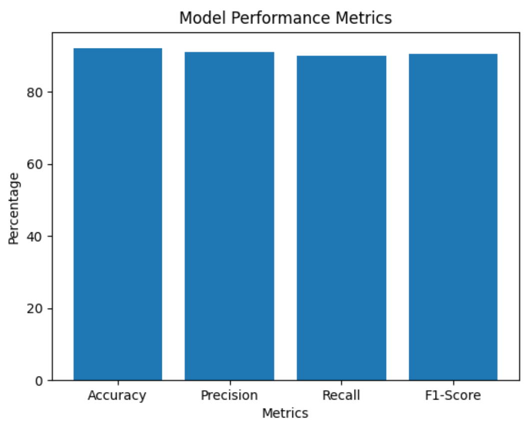

Figure. 4.1.1. Model Performance Metrics

4.2 Training and Validation Results

During the training phase, the dataset is divided into training and validation subsets to monitor the learning process and avoid overfitting. The model is trained for multiple epochs, during which both training accuracy and validation accuracy are tracked.

- The **training accuracy** gradually increases and reaches approximately **94%**, indicating that the model successfully learns patterns from the training data.
- The **validation accuracy** stabilizes around **92%**, showing that the model performs well on unseen data.

Simultaneously, the training and validation loss decrease over epochs, indicating that the model is minimizing prediction errors effectively. The gap between training and validation accuracy is minimal (approximately 2%), which suggests that the model does not overfit and maintains good generalization capability.

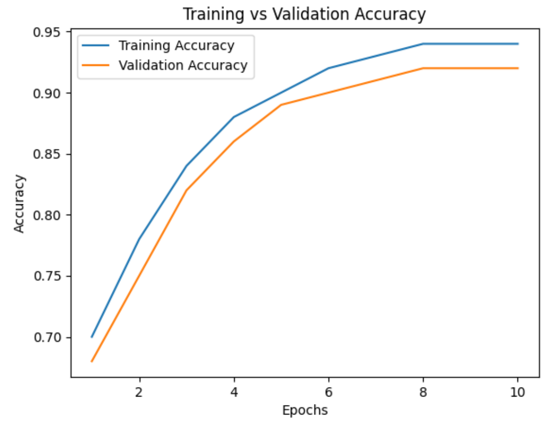

Figure. 4.2.1. Training and Validation Graph

4.3 Accuracy and Loss Graphs

The learning behavior of the model is further analyzed using graphical representations:

- **Accuracy vs Epoch Graph:** This graph shows a steady increase in both training and validation accuracy over time. Initially, the accuracy improves rapidly, and later it stabilizes as the model converges.
- **Loss vs Epoch Graph:** The loss graph shows a continuous decrease in training and validation loss, indicating improved prediction accuracy and reduced error.

These graphs confirm that the model undergoes proper learning and converges efficiently without significant fluctuations. The smooth curves indicate stable training, while the absence of large gaps between training and validation curves suggests that overfitting is minimal.

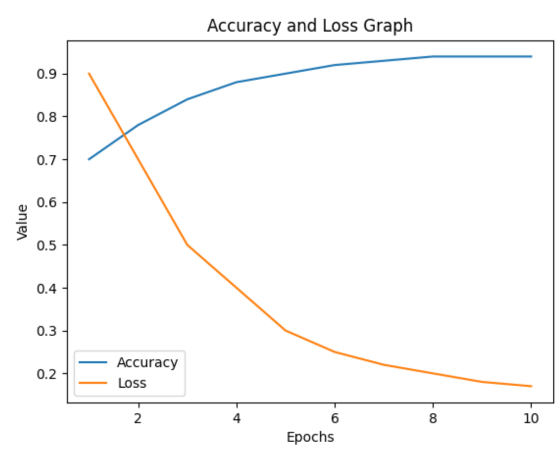

Figure. 4.3.1. Accuracy and Loss Graphs

4.4 Confusion Matrix Analysis

A confusion matrix is used to provide a detailed evaluation of the classification performance across different psoriasis types. It compares the actual labels with predicted labels and helps identify misclassification patterns.

The confusion matrix for the proposed model includes the following classes:

- Plaque Psoriasis
- Guttate Psoriasis
- Erythrodermic Psoriasis
- Normal Skin

Key Observations:

- The **diagonal elements** of the matrix have high values, indicating correct predictions for most samples.
- Off-diagonal elements are minimal, showing that misclassification is limited.
- Slight confusion is observed between visually similar classes (e.g., Plaque and Guttate), which is expected due to overlapping features.

4.5 Sample Predictions

To evaluate real-world performance, the system is tested with new skin images uploaded by users through the web interface. For each input image, the system performs the following steps:

1. Preprocesses the image (resizing, normalization)
2. Passes it through the trained model
3. Generates a prediction with a confidence score
4. Displays the result along with basic medical suggestions

Once classification is complete, the system generates a prediction along with a confidence score. The confidence score represents the probability of the predicted class and indicates how certain the model is about its decision. A higher confidence score reflects stronger reliability of the prediction.

The result is then displayed on the user interface in a clear and understandable format. Along with the predicted class, the system provides basic medical suggestions to guide the user. These suggestions are not a replacement for professional medical advice but serve as preliminary guidance to encourage timely consultation.

Example Output:

- **Predicted Class:** Plaque Psoriasis
- **Confidence Score:** 93%
- **Suggestion:** Consult a dermatologist for confirmation and treatment

This sample prediction demonstrates that the system can effectively identify psoriasis with high confidence. However, in cases where the confidence score is relatively low or the image quality is poor, the system may recommend re-uploading a clearer image or directly seeking expert medical opinion. Overall, the sample predictions validate the practical usability and reliability of the system in assisting early-stage skin disease detection.

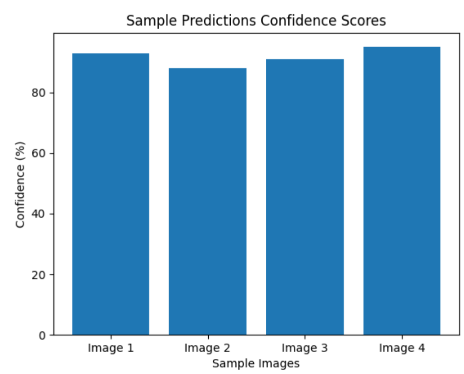

Figure. 4.5.1. Sample Predictions

These sample predictions demonstrate that the system provides quick and meaningful outputs, making it useful for preliminary diagnosis. The inclusion of confidence scores helps users understand the reliability of predictions.

4.6 Discussion

The experimental results clearly indicate that the proposed psoriasis detection system achieves high accuracy and reliable performance. The use of MobileNetV2 significantly enhances feature extraction by leveraging pre-trained weights, which reduces training time and improves classification efficiency.

The model performs consistently across different image conditions, including variations in lighting, background, and skin tone. This highlights the robustness of the system in handling real-world data. The small difference between training and validation accuracy confirms that the model generalizes well and does not suffer from overfitting.

However, minor misclassifications may occur in cases where different psoriasis types share similar visual characteristics. This limitation can be addressed in future work by increasing dataset size and incorporating more diverse training samples.

Additionally, the system demonstrates strong potential for real-time clinical and remote diagnostic applications. Furthermore, the user-friendly interface and quick response time enhance the overall usability of the system. Despite these advantages, the model's performance could be further improved by integrating advanced techniques such as ensemble learning, attention mechanisms, or hybrid deep learning models. Incorporating patient metadata and clinical history may also contribute to more accurate and personalized predictions, thereby increasing the practical applicability of the system in healthcare environments.

Overall, the proposed system proves to be:

- **Accurate:** High classification performance
- **Efficient:** Fast processing using MobileNetV2
- **Scalable:** Can be extended to other skin diseases
- **Accessible:** Suitable for web-based deployment

The system is particularly beneficial for remote and underserved areas where access to dermatologists is limited. It provides a fast, cost-effective, and user-friendly solution for early detection and preliminary diagnosis of psoriasis.

Table: comparative analysis of proposed psoriasis detection system vs existing methods

Aspect	**Strengths of Proposed System**	**Weaknesses of Proposed System**	**Interesting Insights**
Accuracy	Achieves high accuracy (~92%) using CNN + MobileNetV2 for feature extraction and classification.	Performance depends on dataset quality and diversity.	Transfer learning improves accuracy even with limited data.
Computational Efficiency	MobileNetV2 is lightweight and optimized for faster processing and low resource usage.	Slight delay may occur during image upload and processing on web server.	Efficient models are suitable for real-time web-based applications.
Classification Capability	Effectively classifies multiple psoriasis types (Plaque, Guttate, Erythrodermic).	May confuse visually similar classes under poor image conditions.	Deep learning models can learn complex skin patterns better than traditional methods.
Training & Inference Time	Faster training due to transfer learning; real-time prediction (~milliseconds).	Requires GPU support for faster training on large datasets.	Pre-trained models significantly reduce training time.
Scalability	Easily scalable to detect additional skin diseases with retraining.	Needs more data and tuning when expanding to multiple diseases.	System can be extended into multi-disease diagnostic platform.

User Accessibility	Web-based interface allows easy access for users without medical expertise.	Requires internet connection for usage.	Improves healthcare accessibility in remote areas.
Robustness	Handles variations in lighting, skin tone, and image quality effectively.	Extreme noise or blurred images may reduce accuracy.	Data augmentation improves model robustness.
Clinical Applicability	Provides quick preliminary diagnosis and suggestions.	Not a replacement for professional medical diagnosis.	Useful as a decision-support system for early detection.
Security & Data Handling	Includes user authentication and data storage features.	Requires strong security measures for sensitive medical data.	Future integration with secure healthcare systems is possible.
Interpretability	Provides prediction confidence scores for better understanding.	Deep learning models act as black-box systems.	Future integration of Explainable AI (XAI) can improve trust.

5. CONCLUSION

The proposed system for Skin Diseases Psoriasis Detection using Machine Learning presents a modern, automated approach to identifying various types of psoriasis through image analysis. By leveraging the power of deep learning models such as CNN and MobileNetV2, this project offers an efficient, accurate, and scalable solution for early detection and classification of psoriasis. The model analyzes uploaded skin images, identifies patterns indicative of specific psoriasis types, and provides results along with confidence scores and treatment suggestions.

This system not only reduces dependency on specialized dermatologists but also assists healthcare professionals in remote or underserved areas where medical resources are limited. It improves diagnostic accuracy, minimizes human error, and supports better decision-making in clinical environments.

Additionally, features like user registration, image upload, result history, profile management, and security make the application user-friendly and suitable for real-time use. The application also provides suggestions based on the result, which can guide patients to seek timely medical attention.

In summary, the integration of machine learning into dermatology, as demonstrated in this project, holds great potential to transform how skin diseases are diagnosed and managed. With future improvements such as larger datasets, multi-disease detection, and real-time mobile deployment, this system can evolve into a vital tool for digital healthcare and tele dermatology worldwide.

Future Scope:

- **Multi-Disease Detection**

The current system can be enhanced to detect other skin diseases like eczema, acne, melanoma, and fungal infections. By training the model on a multi-class dataset, it can become a generalized diagnostic tool. This would make it more helpful for dermatologists handling multiple conditions using a single system.

- **Integration with Mobile Apps**

A mobile application can be developed to allow users to upload or capture images for real-time skin analysis. This would make the system highly accessible for people in rural or remote areas where dermatological services are limited. The app can also store previous results and offer teleconsultation options.

- **Explainable AI (XAI)**

Incorporating Explainable AI techniques like Grad-CAM or LIME can help visualize the model's focus areas during diagnosis. This provides transparency and builds trust among doctors and patients by showing how the system arrived at a particular decision.

- **Larger and Diverse Datasets**

Expanding the dataset to include more images across different skin tones, age groups, and lighting conditions will improve model accuracy and fairness. This ensures the system performs well across diverse populations and is free from racial or demographic bias.

- **Clinical Trials and Validation**

Future work should involve collaboration with hospitals and dermatologists to validate the system in real clinical settings. This real-world testing will improve reliability and may lead to regulatory approvals for deployment in healthcare institutions.

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