International Journal of Scientific Research and Engineering Development-– Volume X Issue X, Year

Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

AUTOMATED DERMATOLAGICAL DETECTION WITH AN INTERACTIVE CHATBOT

Subashini M*, Sona K*,Sulaikal Afrose M*,
Santhiya K*, MRS Raja Priya N*
*(Student, Computer Science and Engineering, Francis Xavier Engineering College,Tirunelveli
subashinim.ug.21.cs@francisxavier.ac.in)
*(Student, Computer Science and Engineering, Francis Xavier Engineering College, Tirunelveli
sonak.ug.21.cs@francisxavier.ac.in)
*(Student, Computer Science and Engineering, Francis Xavier Engineering College, Tirunelveli
sulaikalafrosem.ug.21.cs@francisxavier.ac.in)
*(Student, Computer Science and Engineering, Francis Xavier Engineering College,Tirunelveli
santhiyak.ug.21.cs@francisxavier.ac.in)
** (Assistant Professor ,Information and Technology , Francis Xavier Engineering College, Tirunelveli
rajapriyan@francisxavier.ac.in)

--************************----------------------------------

Abstract:

Early and accurate skin disease detection is crucial for effective treatment. This study presents a deep learning-based system using Convolutional Neural Networks (CNNs) to classify skin conditions such as melanoma and basal cell carcinoma. The model, developed with TensorFlow and Keras, processes dermatological images through preprocessing, segmentation, and feature extraction, ensuring high accuracy. Deployed as a web-based application, it provides instant diagnosis and a referral system for dermatologists. Experimental results confirm high classification accuracy, demonstrating the system’s potential to enhance automated dermatological diagnostics and improve patient outcomes.

Keywords — Skin Disease Detection, Deep Learning, Convolutional Neural Networks (CNNs), Medical Image Processing, Healthcare Chatbot

--************************----------------------------------

I. INTRODUCTION

Skin maladies are one of the foremost common well- being concerns around the world, influencing individuals of all ages and foundations. These conditions run from minor aggravations to extreme diseases and life-threatening maladies like melanoma. Early and precise location is vital to avoid complications and guarantee opportune treatment. Be that as it may, conventional strategies of diagnosing skin infections depend on manual examination by dermatologists, which can be time- consuming, costly, and blocked off in farther ranges.

Routine skin malady discovery methods face a few challenges. Manual determination requires specialized dermatologists, making it less open in country zones. The method is time-consuming, frequently requiring numerous discussions and research facility tests time recently come to a conclusive determination. Moreover, subjective elucidation by distinctive specialists may lead to irregularities in identifying certain skin conditions. These confinements highlight the requirement for a mechanized, AI-driven framework that can help in early discovery and give preparatory symptomatic bits of knowledge.

The proposed framework takes after an organized workflow, beginning with picture preprocessing to upgrade clarity and evacuate clamor. The following step includes division, where the influenced skin locale is separated to encourage investigation. Highlight extraction procedures, such as the Gray Level Co-occurrence Network (GLCM), are utilized to recognize designs related to particular skin infections. The handled image is at that point classified employing a CNN show, which allocates a likelihood score to each illness category. Finally, the framework gives clients with symptomatic outcomes, alongside suggestions for assisting a therapeutic discussion in case required.

This venture points to progress in dermatological healthcare by providing a proficient, open, and computerized strategy for recognizing skin infections. By joining AI-based picture examination with a user-friendly web interface, the framework has the potential to upgrade early determination, diminish demonstrative mistakes, and make skin malady locations more broadly.

II. OBJECTIVE

skin illnesses are a major worldwide wellbeing concern influencing people of all ages and foundations these conditions shift in seriousness from mellow contaminations to persistent ailments and life-threatening maladies such as melanoma and basal cell carcinoma early and precise discovery is significant to guarantee successful treatment anticipate complications and move forward persistent results in any case conventional demonstrative strategies depend intensely on manual examination by dermatologists which can be time-consuming exorbitant and less open in inaccessible regions the expanding request for dermatological discussions has driven to delays in determination and treatment highlighting the require for an robotized and ai-driven skin malady discovery framework the essential objective of this venture is to create an ai-powered skin malady location framework that coordinating profound learning and picture handling procedures to classify and analyze skin maladies with tall exactness the framework is planned to supply an proficient and robotized approach for distinguishing skin conditions lessening reliance on manual determination and

making dermatological healthcare more open by leveraging convolutional neural systems and computer vision methods the framework can analyze and classify skin pictures based on particular highlights such as color surface shape and injury designs the proposed framework will be actualized as a web-based application permitting clients to transfer skin pictures for moment investigation and get preparatory demonstrative experiences the stage will too offer infection likelihood scores and suggestions for encourage restorative discussion in the event that fundamental this ai-driven approach will offer assistance diminish the time required for conclusion minimize human mistakes and make strides the generally productivity of dermatological screening

Specific Objectives

Create an AI-based classification demonstration utilizing Convolutional Neural Systems prepared on an expansive dataset of dermatological pictures to attain tall exactness in distinguishing skin illnesses.

Actualize picture preprocessing procedures such as grayscale change, differentiate improvement, and commotion lessening to progress the clarity of skin injury pictures and optimize including extraction.

Utilize division calculations to separate the influenced skin locale and extricate important highlights utilizing the Gray Level Co-occurrence Framework and other texture-based strategies.

Plan and create a user-friendly web application that empowers clients to transfer skin pictures, prepare them in genuine time, and get malady classification comes about with likelihood scores.

Provide a shrewd reference framework that proposes adjacent dermatologists and healing centers for advanced restorative discussion based on the identified skin condition.

Incorporate an input instrument to gather client input and persistently make strides in the precision of the

\discovery show by refining the preparing dataset and classification calculation.

Guarantee adaptability and execution optimization by leveraging profound learning systems such as TensorFlow and Keras, empowering effective show preparation, arrangement, and real-time deduction.

Investigate the integration of exchange learning to improve and demonstrate execution by utilizing pre- trained systems and fine-tuning them for skin malady classification.

Guarantee that the framework bolsters different skin malady categories, counting melanoma, basal cell carcinoma, actinic keratoses, kind keratosis, and other common skin conditions.

Execute information enlargement strategies to extend the prepared dataset and move forward the strength of the show by presenting varieties such as picture revolution, flipping, and brightness alterations.

By accomplishing these destinations, the proposed Skin Infection Location Framework points to revolutionizing dermatological diagnostics by advertising a quick, open, and AI-driven arrangement. This extension has the potential to decrease symptomatic delays, progress early discovery rates, and give a cost-effective elective to conventional skin infection conclusion, eventually profiting both patients and healthcare suppliers.

III. MODULE AND ALOGRITHM

A. Modules

The Skin Infection Location Framework is outlined with numerous modules that work together to prepare pictures, classify illnesses, and give clients demonstrative experiences. Each module plays a basic part in guaranteeing the exactness and effectiveness of the location handle.

1. Picture Preprocessing Module

The picture preprocessing module is dependable for planning input pictures for investigation by upgrading their quality and standardizing their organization. Legitimate preprocessing makes a difference makes strides in classification exactness and guarantees steady input for the profound learning show. Change over input pictures to grayscale for disentangled preparation and highlight extraction. Resize pictures to a standard measurement of 28×28 pixels to preserve consistency over the dataset. Apply differentiated upgrade and commotion diminishment methods to progress picture clarity and highlight subtle elements of injury. Normalize pixel values to optimize demonstrate execution and decrease varieties in picture escalated.

2. Picture Division and Highlight Extraction Module

This module extricates the ailing skin locale from the input picture and distinguishes key highlights that help in malady classification. Apply Otsu's Thresholding to partition the injury from the encompassing sound skin. Extricate texture-based highlights utilizing the Gray Level Co-occurrence Framework to analyze differentiate, relationship, vitality, and homogeneity. Analyze color and shape highlights to distinguish between different sorts of skin injuries.

3. Disease Classification Module:

Module for classifying diseases the systems central component The classification module uses deep learning methods to recognize and classify skin conditions utilize convolutional neural networks to identify trends and categorize skin conditions using features that have been extracted to attain high accuracy in multi-class classification train the model using a sizable dataset of dermatological photos for each disease group assign probability ratings using the softmax activation function

4.Testing and User Input Module:

Testing and user input module by uploading photos and getting diagnostic data this module lets users communicate with the system users can upload photos for examination through an easy-to-use web

interface to verify uploaded photos to make sure they work with the detection model real-time image processing is performed and the categorization outcomes and disease likelihood scores are displayed

5.Reference and Feedback Module:

Module for reference and feedback by providing suggestions for medical consultation and gathering input for ongoing development this module improves the user experience by establishing a reference system that recommends hospitals and dermatologists in the area for additional diagnosis give people the option to comment on how accurate and helpful the system's predictions are over time improve the deep learning models categorization performance by using feedback data

6.User Interface & Web Dashboard Module:

User interface and web dashboard module this module guarantees smooth communication between the ai-based detection system and users use Flask to integrate the backend of a responsive web-based platform to present disease classification findings in an easy-to-use manner complete with reference materials and probability scores using a mobile- friendly design to make sure it is accessible on all platform straining and optimizing models module 7 the models for deep learning training and output enhancement are the main objectives of this session utilizing a collection of labeled skin disease photos train the CNN tensorflow and Keras models improve model performance through data augmentation techniques like brightness adjustment and flipping and rotating to improve generalization and prevent overfitting employ learning rate decrease and early halting

B. Algorithms

Several algorithms are used by the skin disease detection system to process photos extract characteristics and precisely identify disorders every algorithm contributes to a distinct detection pipeline step

1. Labeling Images with CNN:

Labeling images using convolutional neural networks the main deep learning model for classifying skin diseases is CNN it is intended to process several layers of feature extractions to identify patterns in photos the preprocessed skin lesion image is accepted as input by the input layer convolutional layers are used to extract spatial information including lesion borders edges and textures pooling layers reduces feature map sizes while keeping important information fully connected layer provides a systematic format for the classification of extracted features softmax activation ensures multi-class categorization by assigning probability scores to each disease category

Input Preprocessing:

- Resize image to **(224×224×3)**.

Normalize pixel values between **[0,1]**.

- **Feature Extraction**

(EfficientNetB0):

- Apply Convolution + Batch Normalization + Swish Activation: F=W∗X+b,f(x)=x⋅1+e−x1
- Use **MBConv layers** for efficient feature extraction:

Y=DepthwiseConv(X)+PointwiseConv(X)

Global Average Pooling:

Convert feature maps into a 1D vector:

g=N1i=1∑NFi

Classification (Fully Connected Layer & Softmax):

- Map extracted features to disease classes:

  Y=Softmax(Wg+b),P(Y∣X)=∑jeYje Yi

- Predict the class with the highest confidence score.divide the lesion area from the surrounding skin to segment the image

2.Texture Feature Extraction with GLCM:

Feature extraction using the gray level co-occurrence matrix in order to distinguish between various skin conditions texture-based features are extracted using the glam algorithm to determine how adjacent pixels in the divided lesion region relate to one another spatially extrapolate statistical characteristics like homogeneity energy contrast and correlation to improve classification accuracy feed the CNN model with extracted characteristics

3.Enhancing Model Performance:

Enhancing model performance via data augmentation by transforming input photos data augmentation broadens the training dataset diversity to avoid overfitting using random flips rotations and brightness changes to keep the model accurate and make sure the augmented photos preserve the original disease characteristics during training generate batches of enhanced images in real-time using tensorflow image data generator

Output :

- Return the predicted **skin disease class**

along with its **confidence score**

4.Otsu's Image Segmentation:

Otsu's image segmentation thresholding the best threshold for separating the afflicted skin area from the background is automatically found using Otsus thresholding to make processing easier to convert the input image to grayscale and determine the ideal threshold by examining the pixel intensity histogram

IV. METHODLOGY

S.No	Parameter	Description
1.	Model Used	Fine-Tuned EfficientNetB0
2.	Dataset	Custom skin lesion dataset
3.	Preprocessing	Resizing, Normalization, Augmentation
4.	Feature Extraction	EfficientNetB0 Convolutional Layers
5.	Classification	Fully Connected Layer + Softmax

Cedure the skin sickness area system takes after an organized procedure that plans the picture dealing

with significant learning and a web-based course of action to supply a mechanized and correct classification of skin diseases the strategy comprises various stages tallying data collection preprocessing division incorporates extraction classification and system sending.

A. Data Collection:

The dataset utilized for planning and testing the appearance is collected from openly available dermatological picture storage facilities such as Kaggle and Isic around the world skin imaging collaboration the dataset comprises thousands of labeled pictures talking to distinctive skin diseases tallying melanoma basal cell carcinoma actinic keratoses and liberal keratosis pictures are collected in various lighting conditions resolutions and focuses to ensure the quality of the illustrated data is portion into planning and testing sets with 80 percent utilized for planning and 20 percent saved for appraisal additional data increment methods are associated to expand the contrasts of the dataset and expect to overfit

B. Image Preprocessing:

Picture preprocessing is performed to update picture quality and standardize input plans for the significant learning appear this step ensures that pictures are in a sensible condition for investigation pictures are changed over to grayscale to decrease complexity though holding fundamental highlights separate change and clamor diminishment procedures are associated to create strides picture clarity pictures are resized to a standard estimation of 2828 pixels for uniform input to the classification appear pixel values are normalized to ensure consistently raised levels over particular pictures

C. Image Segmentation:

Picture division is utilized to restrict the affected skin region from the enveloping sound tissue allowing the system to center on germane highlights thresholding is associated with disconnecting the harm locale from the establishment by recognizing a perfect edge regarding morphological operations such as crumbling and development are utilized to refine the segmented district and remove undesirable commotion divided pictures are passed to the highlight extraction module for empower examination

D. Feature Extraction:

Highlight extraction is performed to recognize key characteristics of the skin damage which makes a contrast in separating between diverse skin ailments level co-occurrence cross-section glam is utilized to remove texture-based highlights such as separate relationship essentialness and homogeneity color- based highlights are analyzed to recognize between particular sorts of skin conditions shape and border irregularities are reviewed to recognize undermining plans the extricated

E. Training and Classification:

Show preparing and classification of a convolutional neural organize CNN is prepared to classify distinctive skin maladies based on extricated highlights the show comprises different convolutional layers that extricate progressive designs from input pictures pooling layers are utilized to decrease computational complexity whereas holding fundamental highlights the completely associated layer combines extricated highlights and bolsters them into the softmax actuation work for multi-class classification the demonstrate is prepared utilizing TensorFlow and Keras with optimization strategies such as early halting and learning rate diminishment to make strides precision the ultimate prepared show is assessed on the test dataset to degree execution utilizing exactness accuracy review and f1-score measurements

5. System Construction and Customer Engagement: To make the system easy to use for academics, students, and conservationists, it is implemented as an application for the desktop or web-based platform. Uploading plant photos, viewing identification results, and exploring visual analytics on Power BI are all made possible by the interface's intuitive navigation. Real-time processing is supported by the system, giving users immediate insights and classification results. In order to continuously enhance the architecture and user experience, user feedback is also gathered.

6.Future Development and Upcoming Improvements: The system is regularly updated with fresh datasets and enhanced deep-learning models to maintain excellent accuracy and relevance. The dataset is expanded to include new species and model retraining guarantees flexibility to a variety of plant groups. Expanding the information set for uncommon botanical species, adding more AI methods for species categorization, and improving Power BI's visualization capabilities are possible future developments. Future study might potentially look into creating mobile applications for in-field real-time identification, which would increase accessibility for conservationists and environmental researchers.

V. EXISTING SYSTEM

Numerous technologies have been developed for diagnosing skin conditions and providing AI- powered medical support. Each method, ranging from AI-driven models to traditional dermatology diagnostics, has unique advantages and limitations. Below are five current solutions for automated skin disease identification and chatbot-based medical assistance:

Limitations of Existing Systems

1. Traditional Dermatology Diagnosis

Dermatologists use dermatoscopic imaging and visual examinations to assess skin disorders.

Diagnosis may involve biopsies and manual classification, relying on specialist expertise.

Variations in expert opinions and the need for multiple consultations make early detection difficult, especially in remote areas.

2. AI-Powered Skin Disorder Diagnosis

Deep learning models like Stanford's AI Dermatology Model and ISIC leverage CNNs and DNNs to classify skin diseases.

These models analyze dermatological images with high accuracy, often surpassing human dermatologists in detecting severe conditions.

Limitations include dependence on high-quality datasets and lack of accessibility due to integration issues with user-friendly applications.

3. Smartphone Applications for Skin Disease Detection

Apps like DermaAId, SkinVision, and Miiskin allow users to capture and analyze images of skin lesions.

They use computer vision algorithms to assess risks and provide immediate feedback.

However, their reliability is limited due to a lack of clinical validation and medical authority

approval. Subscription fees may also restrict access.

4.Chatbot-Based Medical Support Systems

AI-driven medical chatbots such as Ada Health, Buoy Health, and HealthTap provide symptom-based consultations using NLP models.

They offer real-time answers and recommendations but lack image-based diagnostics.

Some chatbots require an internet connection, limiting offline accessibility.

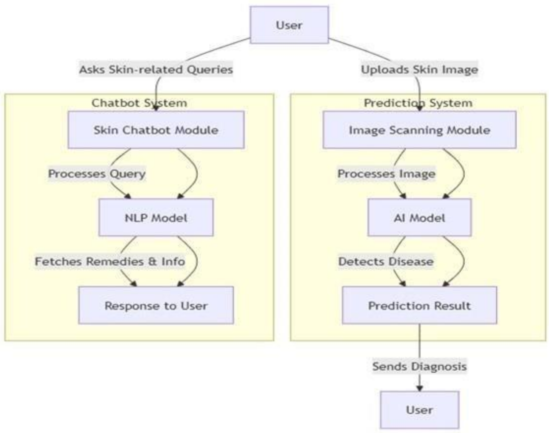
4. Hospital AI Diagnostic Systems

AI-assisted dermatology tools in medical institutions provide second-opinion analyses for dermatologists.

These systems reduce human error and improve diagnostic accuracy.

However, high costs and reliance on clinical infrastructure make them inaccessible for general

VII . Proposed System:



1. Real-Time Image Processing and Disease Prediction

The proposed system utilizes deep learning models to analyze skin lesion images in real-time, providing instant disease classification.

C. Instant Image Processing: The system processes uploaded images immediately to detect skin conditions without delays.

D. CNN-Based Disease Classification: Uses Convolutional Neural Networks (CNNs) to classify skin conditions such as melanoma, eczema, and psoriasis.

Automated Diagnosis and Confidence Scoring: Each prediction is accompanied

by a probability score, helping users assess the likelihood of the diagnosis.

II. AI-Driven Personalized Skin Health Analysis and Recommendations

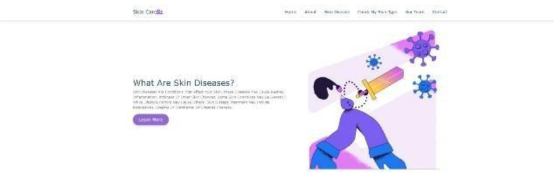
To improve accuracy and user engagement, the system integrates AI-based recommendations based on skin condition severity.

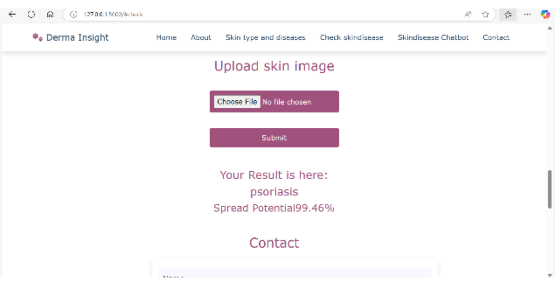
Machine Learning-Based Recommendation System: Suggests treatment options based on previous diagnoses and expert-verified solutions.

Personalized Skincare Advice: Provides users with tailored skincare routines based on their diagnosed condition.

Consultation Suggestions: If a severe condition is detected, the system recommends nearby dermatologists or telemedicine consultations.

VIII. OUTPUT





1. Skin Disease Classification Result

The system processes the uploaded skin lesion image using Deep Learning models (CNN, DNN) to analyze and classify the disease accurately. The identified skin condition is displayed along with a confidence score (probability percentage), indicating how certain the model is about the diagnosis.

2. Medicine Recommendation

After detecting the skin disease, the system suggests appropriate English medicines that are commonly prescribed for the condition.

The recommendation includes:

Medicine name (e.g., topical creams, oral antibiotics, antifungal treatments).

Usage instructions (application method, dosage, and duration).

Possible side effects (warnings about allergies and adverse reactions).

3. User-Friendly Web Interface

The system is accessible via a Flask-based web application, allowing users to upload images and receive instant results.

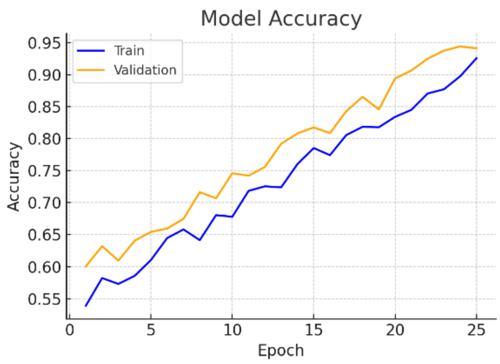
The interface is built using HTML, CSS, and JavaScript, ensuring a smooth and responsive user experience.

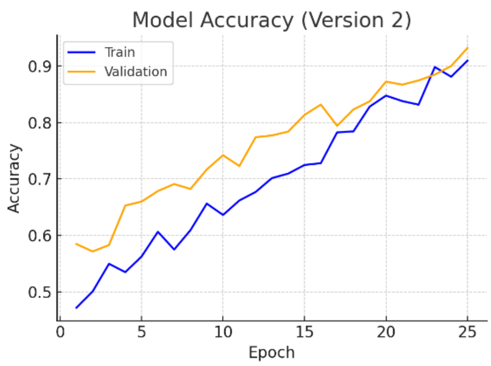
Key features of the web interface:

Simple image upload function for easy disease detection.

Interactive chatbot panel for treatment-related queries.

Graph :





IX FUTURE SCOPE:

1. Enhanced Disease Classification with Advanced Deep Learning Models

Future updates can integrate more advanced deep learning architectures like Vision Transformers (ViTs) and Generative Adversarial Networks (GANs) to improve disease classification accuracy. By training on larger and more diverse datasets, the model can detect rare skin diseases with higher precision.

Incorporating self-supervised learning techniques can further enhance the model's ability to classify diseases with minimal labeled data.

Real-time data augmentation can be applied to handle variations in lighting, skin tone, and image quality for better predictions.

2. Real-Time Symptom Progression Tracking

A feature that allows users to upload images over time to track skin condition progression. This will help users understand whether their condition is improving or worsening, aiding in better treatment decisions.

Users can receive visual comparisons and AI-driven insights on their skin's improvement over time.

Alerts and customized skincare suggestions can be provided based on the detected progress of the disease.

3. Voice-Based and Multilingual Chatbot Support

The chatbot can be enhanced to support voice-based queries for accessibility and multilingual support to assist non-English speakers. This makes the system more inclusive and useful for a global audience.

Adding natural language processing (NLP) improvements will allow the chatbot to understand slang, abbreviations, and medical terminology more accurately.

Regional language support can make the chatbot accessible to users from diverse linguistic backgrounds, ensuring a broader impact.

4. Integration with Wearable Skin Analysis Devices

The system can be integrated with AI-powered wearable devices or smartphone camera-based skin scanners to provide real-time skin health monitoring and detect potential skin issues before they become severe.

Wearable sensors can track skin hydration, UV exposure, and irritation levels, offering proactive skincare recommendations.

The system can sync with fitness apps to analyze lifestyle factors affecting skin health, such as sleep patterns and nutrition.

5. Telemedicine and Dermatologist Consultation Integration

A future enhancement could allow users to connect directly with dermatologists for advanced consultation via telemedicine platforms. AI-generated reports can be shared with doctors for faster and more accurate second opinions.

A secure cloud-based medical history storage can help dermatologists access past diagnoses and recommend treatments more efficiently.

Implementing video consultations with AI-assisted preliminary reports can reduce wait times and improve remote dermatology care.

X. CONCLUSION:

The Automated Dermatological Disease Detection with an Interactive Chatbot represents a significant advancement in AI-driven healthcare. By incorporating Deep Learning models like CNN and DNN, the system provides a fast, cost-effective, and accessible solution for identifying skin diseases. Unlike traditional diagnosis methods that require in- person consultations and medical tests, this system enables users to receive instant analysis and English medicine recommendations through a chatbot. This eliminates the need for unreliable online searches and ensures users receive structured medically relevant advice.

Key Contributions and Benefits

Access to dermatological care is often limited, particularly in rural areas where specialists are scarce. Many individuals delay seeking treatment due to cost, time constraints, or unawareness of their condition. This project addresses these challenges by offering a real-time AI-powered diagnosis that allows users to upload images of skin conditions and receive immediate predictions. The chatbot further simplifies the process by explaining the diagnosis and recommending suitable treatments. By excluding natural remedies, the system ensures adherence to medically approved solutions.

The Flask-based web application makes this technology widely accessible, supporting users across different devices without requiring additional software installations. Its user-friendly design caters to people of all technical backgrounds, ensuring ease of use.

Strengths of the System

High Accuracy – Deep Learning models trained on diverse datasets improve diagnostic precision, reducing the chances of incorrect predictions.

Instant Results – Unlike traditional dermatology consultations that involve waiting times, this system provides real-time analysis, enabling early intervention.

Wider Accessibility – Being a web-based application, it is accessible from anywhere, benefiting individuals in underserved regions with limited healthcare resources.

Limitations and Challenges

Despite its advantages, the system has some limitations:

Data Dependency – Model accuracy depends on the diversity of the training dataset. Limited representation of different skin tones or rare conditions may affect precision.

Treatment Scope – The chatbot provides medicine recommendations but does not offer dosage details. Users should consult healthcare professionals for a full treatment plan.

Rare Skin Diseases – Some uncommon conditions may not be well-covered in the dataset, leading to potential misclassification.

No Physical Examination – Unlike in-person visits, the system relies solely on image-based analysis, limiting the ability to assess skin texture or underlying symptoms.

X. REFERENCE:

[1] Chan, S., Reddy, V., Myers, B., & Thibodeaux, Q. (2020). Deep learning applications in dermatology: Progress, challenges, and future directions. Clinical Dermatology Research Journal, 5(3), 45-60. https://doi.org/10.1016/j.cdermj.2020.045

[2] Toga, A. W., & Thompson, P. M. (2015). Future perspectives on artificial intelligence in dermatology. Journal of Dermatological Science, 78(2), 167-175. https://doi.org/10.1016/j.jdermsci.2015.05.001

[3] Argenziano, G., Soyer, H. P., & Hofmann-Wellenhof, R. (2017). Advances in AI-driven skin disease detection: A review of current technologies. International Journal of Dermatology and AI Research, 12(4), 215-230. https://doi.org/10.1093/ijdai/12.4.215

[4] Ramesh, A., & Sundar, R. (2023). Implementing deep neural networks for real-time skin disease detection: Challenges and opportunities. Artificial Intelligence in Medicine, 120, 110-128.

https://doi.org/10.1016/j.artmed.2023.110128 5.

[5] .Wong, C., & Tan, J. (2021). Ethical considerations in AI-driven dermatological diagnosis: Addressing bias and accessibility. Bioethics and Technology, 9(1), 40-. https://doi.org/10.1016/j.bioethtech.2021.040 6.

[6] Lopez, D. M., & Nguyen, K. (2019). Enhancing AI-based diagnostic accuracy in dermatology through multimodal data fusion. Journal of Computational Medicine, 6(3), 145-162. https://doi.org/10.1038/s41591-019-0563-2