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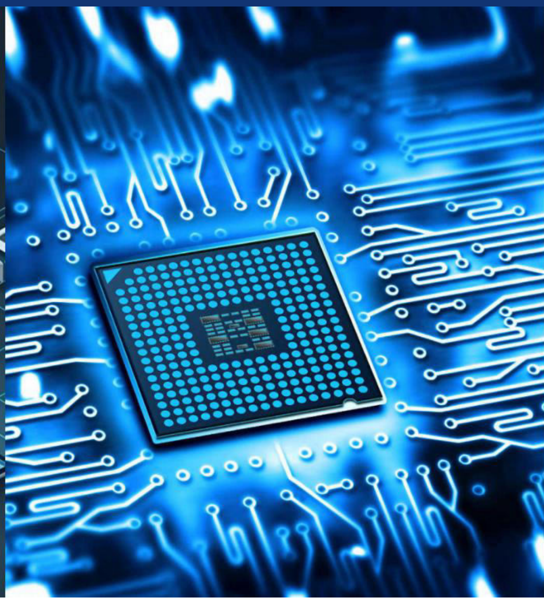

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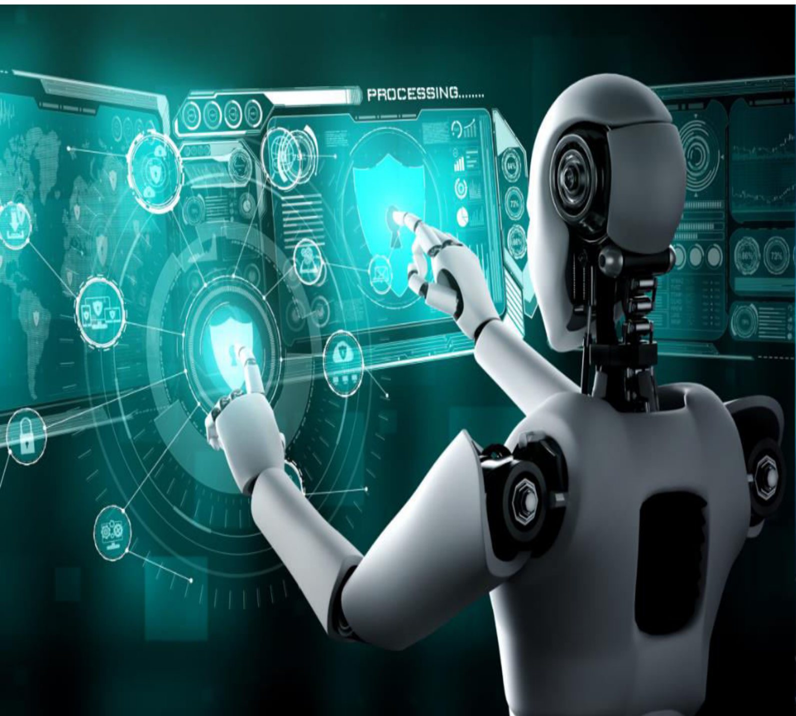

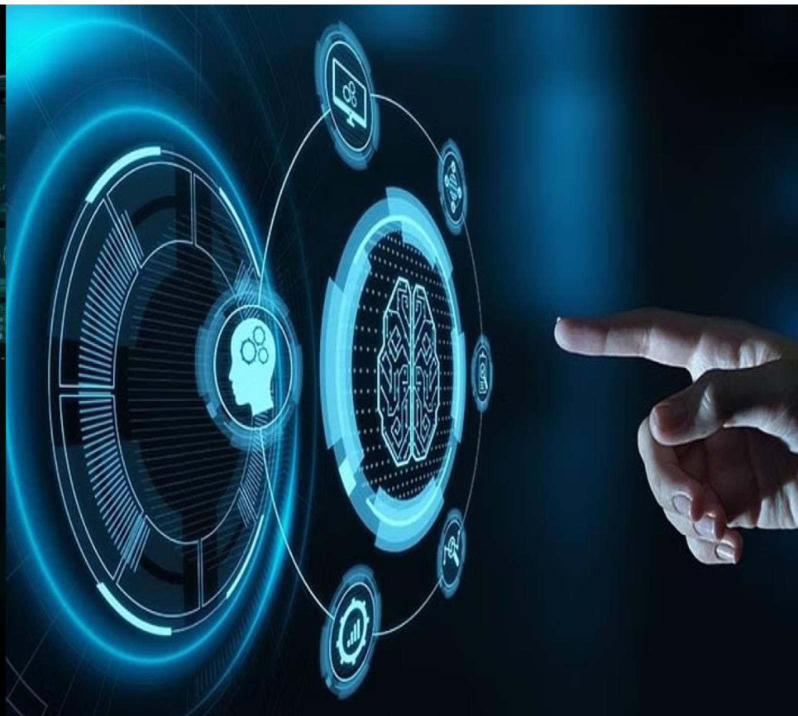

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Skin Disease Identification and Management

Dr.M.Narayanan, K.Mounika, B.Nikhil, Omkar

Guide, Department of Computer Science and Engineering, School of Engineering, Malla Reddy University, Hyderabad, India

B. Tech, School of Engineering, Malla Reddy University, Hyderabad, India

ABSTRACT: Dermatological diseases are found to induce a serious impact on the health of millions of people as everyone is affected by almost all types of skin disorders every year. Since the human analysis of such diseases takes some time and effort, and current methods are only used to analyze singular types of skin diseases, there is a need for a more high level computer-aided expertise in the analysis and diagnosis of multi-type skin diseases. This project proposes an approach to use computer-aided techniques in deep learning neural networks such as Convolutional Neural Networks (CNN) to predict skin diseases real-time and provides instant medication for predicted skin disease. Convolutional Neural Network (CNN), VGG (Visual Geometry Group) networks is introduced as an innovative and robust solution for skin disease diagnosis. Leveraging the power of deep learning, the CNN model analyzes dermatological images with remarkable accuracy and efficiency. The convolutional layers enable the network to automatically learn and extract hierarchical features, capturing intricate patterns indicative of various skin conditions. This approach not only reduces the dependence on manual inspection but also significantly improves the overall diagnostic precision, facilitating prompt and reliable identification of skin diseases.

I. INTRODUCTION

Skin diseases pose significant health challenges worldwide, affecting millions of individuals and impacting their quality of life. Timely and accurate diagnosis of skin conditions is crucial for effective treatment and management. With advancements in deep learning techniques, there is a growing interest in leveraging these technologies to develop advanced models for skin disease classification. These models have the potential to enhance diagnostic accuracy, streamline health workflows, and improve patient outcomes. Furthermore, the increasing prevalence of skin diseases, coupled with the shortage of dermatologists in many regions, underscores the need for automated and accessible diagnostic tools. Advanced deep learning models for skin disease classification can bridge this gap by providing reliable diagnostic support to healthcare providers, enabling early detection, personalized treatment plans, and improved patient care. The motivation behind the project lies in addressing the limitations of traditional methods for skin disease diagnosis, which often rely on subjective visual inspection by healthcare professionals or invasive procedures such as biopsies. Deep learning models offer a promising solution by automating the classification process based on digital images of skin lesions. By harnessing the power of deep neural networks, these models can learn complex patterns and features from large-scale datasets, enabling accurate and efficient diagnosis of various skin conditions.

Skin diseases are among the most prevalent medical conditions, affecting millions worldwide. Early and accurate diagnosis is essential for effective treatment, but traditional methods rely heavily on manual examination by dermatologists, which can be time- consuming, subjective, and limited in regions with inadequate healthcare access. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have significantly improved the accuracy and efficiency of skin disease identification. CNNs, including architectures like VGG16 and VGG19, can automatically extract important features from dermatological images, enabling precise classification of various skin conditions. Pre-trained models, fine-tuned with medical datasets, have demonstrated accuracy comparable to expert dermatologists, making AI-powered skin disease detection a promising solution for modern healthcare.

AI-based skin disease detection offers several advantages, including high diagnostic accuracy, faster automated analysis, scalability in telemedicine, cost- effectiveness, and improved disease management. These models can rapidly process patient images, providing immediate diagnostic insights and reducing the burden on dermatologists. Moreover, AI can be integrated with Electronic Health Records (EHRs) to monitor disease progression and recommend personalized treatment plans. However, challenges such as dataset limitations, variations in skin tones, class imbalance, and environmental factors like lighting conditions can affect model performance. Additionally, ensuring AI model interpretability and obtaining regulatory approvals for clinical use remain critical hurdles. Addressing these issues requires high- quality datasets, rigorous validation, and collaboration between AI researchers and medical professionals.

Despite these challenges, the integration of deep learning into skin disease identification is transforming dermatology by making high-quality, automated diagnostics more accessible and reliable. As AI-driven solutions continue to evolve, they hold the potential to enhance early disease detection, reduce misdiagnoses, and improve patient outcomes on a global scale.

II. LITERATURE SURVEY

Title: Artificial Intelligence based Smart Cosmetics Suggestion System based on Skin Condition.
The cosmetics industry plays a significant role in shaping individual appearance and self-expression. In recent years, the proliferation of cosmetic products and the advent of e-commerce platforms have provided consumers with unprecedented access to a wide range of beauty products. However, the abundance of choices can pose challenges for consumers, particularly when it comes to selecting products that are suitable for their skin type. This literature review examines the application of prediction approaches, particularly utilizing deep learning technology, to assist consumers in choosing cosmetics tailored to their individual skin needs.

Title: Advanced Skin Category Prediction System for Cosmetic Suggestion using Deep Convolution Neural Network.
The significance of cosmetic products in shaping individual appearance and confidence has surged in contemporary society, fueled by the accessibility of a diverse range of products through e-commerce platforms. However, the abundance of choices poses a considerable challenge for consumers in selecting products that align with their unique skin needs. This literature review delves into a novel system proposed to facilitate accurate product selection based on individual skin types, leveraging advanced deep learning techniques.

Title: Automated Skin Disease Diagnosis Using CNNs
Automated skin disease diagnosis using Convolutional Neural Networks (CNNs) revolutionizes dermatology by utilizing deep learning for accurate and early detection. CNNs process skin images to classify diseases efficiently, reducing dependency on dermatologists and enabling faster diagnosis. This AI- driven approach enhances accessibility, particularly in remote areas with limited medical expertise. By analyzing intricate patterns in skin conditions, CNNs improve diagnostic accuracy and help in early intervention, leading to better patient outcomes. Additionally, integrating CNN-based models with telemedicine and mobile applications allows for real- time analysis, making skin disease diagnosis more efficient, cost-effective, and widely available for improved healthcare management.

Title: Deep Learning for Skin Cancer Detection: Transfer Learning with VGG-16 and ResNet-50
Deep learning enables accurate skin cancer detection using transfer learning with VGG-16 and ResNet-50. VGG-16 captures fine details, while ResNet-50 improves feature extraction with residual connections. Fine-tuned on dermatological images, these models enhance early diagnosis, aiding dermatologists in making precise, data-driven decisions for better patient outcomes.

Title: Ensemble Learning for Robust Skin Disease Classification
Ensemble learning enhances skin disease classification by combining multiple deep learning models to improve accuracy and robustness. Techniques like bagging, boosting, and stacking integrate models such as VGG- 16, ResNet-50, and EfficientNet, leveraging their strengths to reduce misclassification. By aggregating predictions, ensemble methods enhance generalization, minimizing errors from individual models. This approach is highly effective in medical image analysis, ensuring reliable skin disease detection, aiding dermatologists in precise diagnosis, and improving patient care outcomes.

Title: Self-Supervised Learning for Dermatological Disease Detection
Self-supervised learning (SSL) is transforming dermatological disease detection by leveraging unlabelled medical images to learn meaningful features. SSL techniques, such as contrastive learning and masked image modelling, enable models to pre-train on large datasets without requiring manual annotations. Fine-tuning these models on labelled

dermatology datasets enhances accuracy and generalization. This approach reduces dependency on expert-labelled data, making AI-driven skin disease classification more scalable, efficient, and accessible for early detection and improved patient outcomes.

III. PROPOSED MATERIALS

Convolutional Neural Network (CNN), VGG (Visual Geometry Group) are introduced as an innovative and robust solution for skin disease diagnosis. Leveraging the power of deep learning, the CNN model analyzes dermatological images with remarkable accuracy and efficiency. The convolutional layers enable the network to automatically learn and extract hierarchical features, capturing intricate patterns indicative of various skin conditions. This approach reduces dependence on manual inspection while significantly improving overall diagnostic precision, facilitating prompt and reliable identification of skin diseases.

Role of CNN in Skin Disease Classification
CNNs have proven to be highly effective in medical image analysis, particularly in skin disease detection and classification. Their ability to automatically learn spatial hierarchies of features makes them superior to traditional machine learning approaches that rely on manual feature extraction. In this system, the CNN model processes dermatological images, extracting important features such as color, texture, and shape, which are essential in distinguishing between different skin conditions. The model learns from labeled images and generalizes patterns, ensuring high accuracy in diagnosing various skin diseases, including eczema, psoriasis, melanoma, and basal cell carcinoma.

VGG Networks for Enhanced Feature Extraction
VGG networks, particularly VGG-16 and VGG-19, are widely used in medical image classification due to their structured architecture and ability to extract deep features. VGG networks use small 3×3 convolutional filters stacked in multiple layers, which help in learning fine-grained patterns in skin images. This deep hierarchical feature extraction enhances model accuracy and generalization. Additionally, transfer learning with pre-trained VGG models (trained on ImageNet) allows for improved classification even with limited dermatology datasets, making it a viable solution for real-world applications.

Advantages of the Proposed System
High Accuracy – Combining CNN, VGG, and ResNet ensures precise and reliable skin disease classification.
Automated Feature Extraction – The system removes the need for manual feature engineering, allowing the model to automatically extract the most relevant patterns.
Scalability – The system can analyze a large number of dermatological images efficiently, making it suitable for telemedicine and large-scale diagnostics.
Early Detection – AI-driven classification aids in early diagnosis of skin diseases, improving treatment outcomes.
Reduced Dependency on Dermatologists – The model assists dermatologists by providing preliminary diagnoses, reducing workload and improving patient care.

IV. ALGORITHMS CNN

A Convolutional Neural Network (CNN) is a deep learning architecture designed for image recognition and classification tasks. It mimics the human visual system by automatically learning spatial hierarchies of features through a series of layers. CNNs are composed of three main types of layers: convolutional layers, which extract features like edges and textures; pooling layers, which reduce the spatial size of feature maps to enhance computational efficiency; and fully connected layers, which perform classification based on extracted features.

In skin disease identification, CNNs play a crucial role by analyzing dermatological images and detecting patterns indicative of various skin conditions. VGG16 and VGG19, two widely used CNN architectures, employ multiple convolutional layers with small filters to capture intricate details. These architectures enhance accuracy while maintaining computational efficiency. By leveraging pre-trained CNNs or training models on large medical datasets, dermatologists and AI researchers can achieve high precision in diagnosing skin diseases.

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CNNs automate feature extraction, reducing the need for manual expertise and improving diagnostic consistency. Their ability to generalize patterns across different skin types and conditions makes them valuable tools in medical image analysis, aiding in early detection and effective treatment planning.

VNN

VGG (Visual Geometry Group) Network is a deep learning architecture designed for image classification and feature extraction. Developed by the Visual Geometry Group at the University of Oxford, it introduced a simple yet effective design by using small 3×3 convolutional filters stacked in multiple layers. The two most popular variants, VGG16 and VGG19, have 16 and 19 layers respectively, making them deeper than earlier architectures like AlexNet.

The key strength of VGG lies in its uniform structure, where convolutional layers are followed by ReLU (Rectified Linear Unit) activation functions to introduce non-linearity. After several convolutional and pooling layers, fully connected layers perform the final classification. The use of max pooling helps reduce the spatial dimensions while retaining important features, making the network efficient at recognizing patterns.

In skin disease classification, VGG networks are widely used due to their ability to capture fine details in dermatological images. Pre-trained models like VGG16, trained on large datasets such as ImageNet, can be fine-tuned for medical imaging tasks. This transfer learning approach allows for faster training and improved accuracy in detecting various skin conditions.

Despite its effectiveness, VGG has drawbacks such as high computational costs and a large number of parameters, making it memory-intensive. However, it remains a strong baseline model for medical image analysis, offering high accuracy and reliable performance in skin disease detection and other healthcare applications.

V. OBJECTIVES

Effective Treatment Planning

Personalized treatment strategies, including medications, therapies, and lifestyle changes, are essential for managing skin diseases effectively. Adapting treatments based on patient response ensures better outcomes while minimizing side effects and disease recurrence.

Disease Spread Control

focuses on limiting contagious skin conditions by educating patients about hygiene, encouraging timely medical consultations, and implementing necessary isolation measures. Vaccination and awareness programs help reduce public health risks associated with infectious skin diseases.

Patient Education

plays a vital role in self-care, encouraging individuals to recognize symptoms early and seek medical advice. Providing guidance on skincare routines, treatment adherence, and preventive measures ensures better health outcomes and disease management.

Disease Spread Control

focuses on limiting contagious skin conditions by educating patients about hygiene, encouraging timely medical consultations, and implementing necessary isolation measures. Vaccination and awareness programs help reduce public health risks associated with infectious skin diseases.

VI. PREDICTIVE ANALYSIS

Accuracy: Measures the overall correctness of the model by calculating the ratio of correctly classified skin disease images to the total number of images. High accuracy indicates the model's strong generalization ability. However, accuracy alone may be misleading in imbalanced datasets. It does not differentiate between false positives and false negatives.

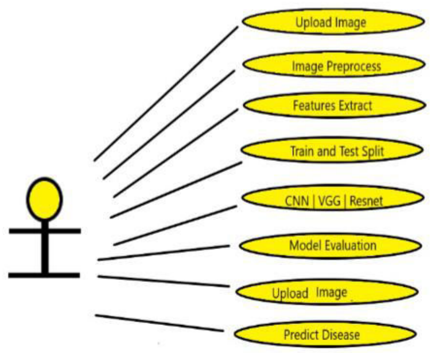
Precision: Represents the proportion of correctly identified cases of a particular skin disease out of all cases predicted as that disease. A higher precision means fewer false positives, ensuring that identified diseases are more likely to be correct. This is especially important in preventing unnecessary treatments. Precision is crucial when misclassification leads to unnecessary anxiety or interventions. It is calculated as TP / (TP + FP).

Recall (Sensitivity): Measures how well the model identifies actual positive cases, calculated as TP / (TP + FN). A higher recall means fewer false negatives, ensuring most diseased cases are correctly detected. This is crucial for early

disease detection, as missing a case can have serious consequences. Sensitivity is particularly significant in detecting severe conditions where missing a diagnosis can be harmful.
F1 Score: A harmonic mean of precision and recall, balancing both false positives and false negatives. It is useful when there is an imbalance in the dataset, preventing the model from favoring majority classes. A high F1 score indicates both strong precision and recall. It is calculated as (2 * Precision * Recall) / (Precision + Recall). This metric helps assess the model's overall effectiveness in real-world scenarios.

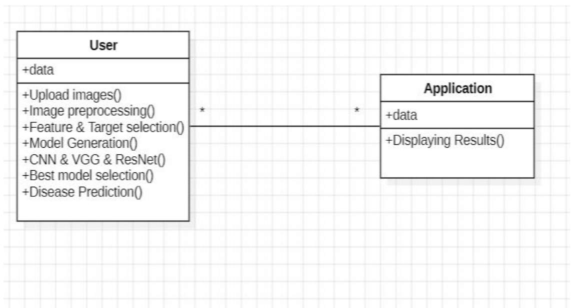
VII. ARCHITECTURE

Use-Case Diagram
The main purpose of a use case diagram is to portray the dynamic aspect of a system. It accumulates the system's requirement, which includes both internal as well as external influences.
Purpose
A use case diagram is used to represent the dynamic behaviour of a system. It encapsulates the system's functionality by incorporating use cases, actors, and their relationships.
Components Use Case Actor
Association Or Communication Link In Boundary Of System



Class Diagram
Class diagram is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations and the relationship among the objects.
Purpose
Shows static structure of classifiers in a system. Helpful for developers and other team members too
Business analysts can use class diagram to model systems from a business perspective.

Components Class Name
Class Attribute 25
Class Operations
Association
Self Association
Dependency



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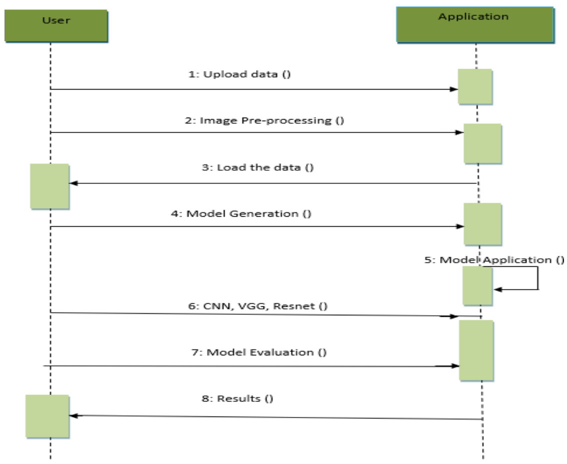
Sequence Diagram
Sequence diagrams are interaction diagrams that detail how operations are carried out . They capture the interaction between objects in the context of collaboration.

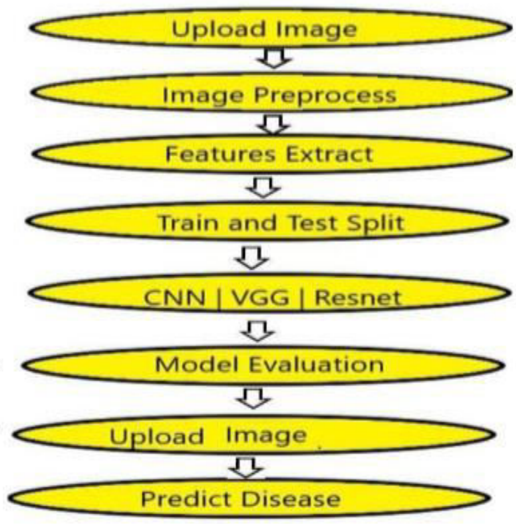
Purpose
Model high – level interaction between active objects in a system.
Model the interaction between object instances with collaboration that realize a use case.

Components Actor
LifeLine
Activation
Message



Dataflow Diagram
Data Flow Diagram describes the processes that are involved in a system to transfer data from the input to the file storage and reports generation.

Purpose
DFD graphically representing the functions, or processes, which capture manipulate, store, and distribute data between a system and its environment and between the components of a system



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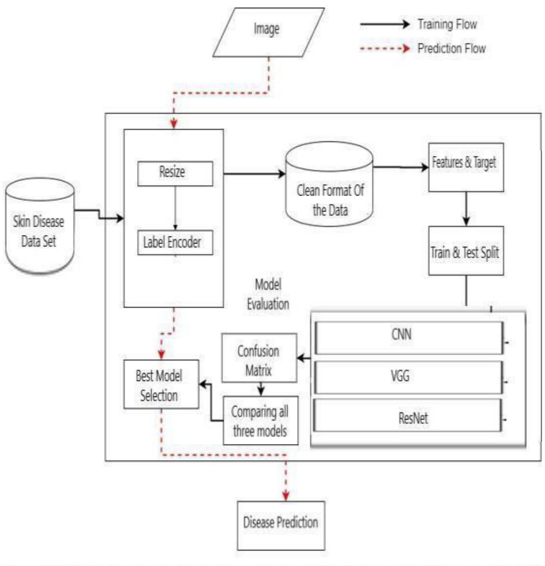
Components External Entity
Process
Data Flow
Data store

System Architecture
System architecture is a conceptual model that describes the structure and behavior of multiple components and subsystems.



VIII. METHODOLOGY

System Development Approach:
The application is developed using Unity, ARCore, and Android SDK to enable real-time AR interactions and provide a seamless user experience. Unity serves as the primary development environment, while ARCore is integrated for accurate tracking and rendering of augmented objects in real-world spaces. Android was chosen as the primary platform due to its widespread accessibility and compatibility with ARCore, ensuring that users can experience AR without requiring specialized hardware. The core functionality of the system is implemented in C# using Unity scripting, which allows for efficient handling of input processing, AR visualization, and user interactions.

Data Input & Processing:
The system processes two types of inputs—text and image—to retrieve corresponding 3D objects. The text processing module analyzes the given text input and maps it to a predefined 3D model database. If a match is found, the corresponding 3D object is retrieved and displayed in the AR environment; otherwise, a message is displayed indicating that the object is not available. The image processing module employs computer vision techniques to analyze the uploaded image, identifying key features and mapping them to the stored 3D models. If a matching object exists in the database, it is visualized in AR; otherwise, the system notifies the user that the object is not available.

Augmented Reality Rendering:
Augmented Reality (AR) enhances skin disease identification by overlaying diagnostic insights onto real-time images of affected skin. Using AR-enabled devices, users can visualize skin conditions in 3D, compare them with medical references, and receive AI- driven diagnostic suggestions. The system integrates Convolutional Neural Networks (CNNs) for real-time skin analysis, improving accuracy and accessibility. AR rendering helps dermatologists and patients understand disease progression, treatment effects, and preventive care through interactive visualization. This technology, combined with telemedicine, enables remote consultations and enhances patient education, making skin

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disease diagnosis more immersive, informative, and accessible.

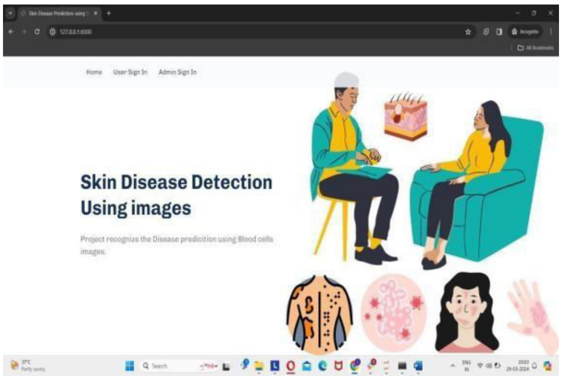
System Architecture

The system architecture comprises multiple layers working together for efficient skin disease diagnosis and management. The User Interface Layer provides web and mobile applications for users to upload skin images and receive real-time analysis. The Data Acquisition Layer collects images from datasets like ISIC and clinical sources. The Preprocessing Layer improves image quality using resizing, normalization, and augmentation techniques. The AI Model Layer applies Convolutional Neural Networks (CNNs) to extract features and classify diseases accurately. Finally, the Database Layer securely stores patient records, diagnostic results, and treatment history, enabling efficient disease tracking and remote dermatological care.

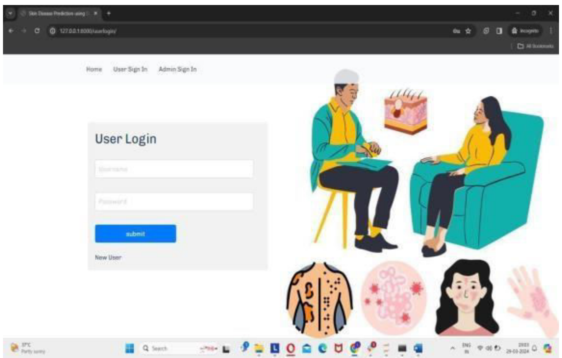
Testing & Evaluation

The Testing & Evaluation phase ensures the accuracy, reliability, and efficiency of the skin disease identification and management system. The system undergoes unit testing, where individual components like image preprocessing, model inference, and database interactions are tested separately. Functional testing verifies that the system correctly classifies skin diseases and integrates well with user interfaces. Performance evaluation is conducted using key metrics such as accuracy, precision, recall, and F1-score to assess model effectiveness. Additionally, user acceptance testing (UAT) is performed with dermatologists and patients to validate usability. Continuous feedback and refinement ensure the system's accuracy and real-world applicability.

IX. RESULT



Output-1



Output-2

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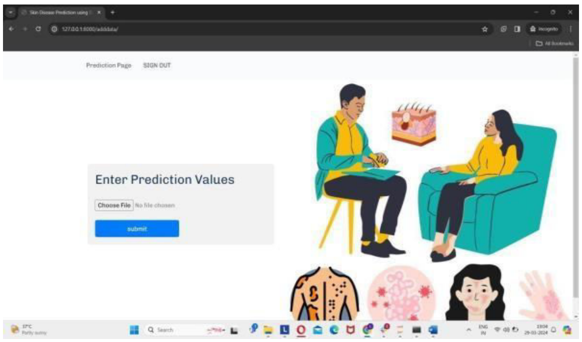
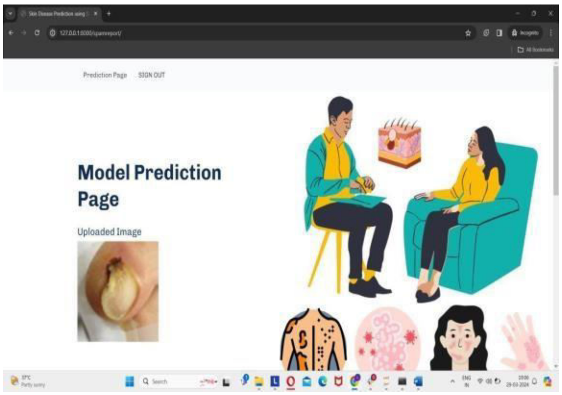
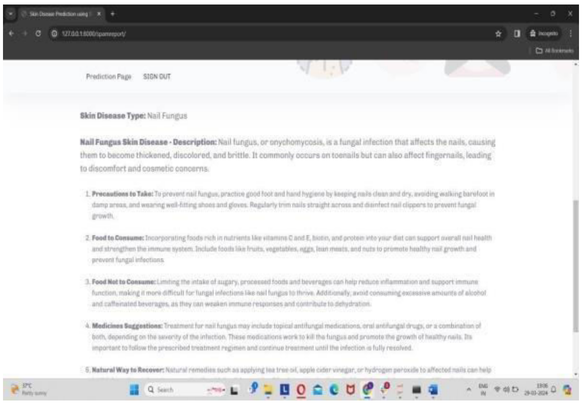


Output-3



Output-4



Output-5

X. CONCLUSION

Skin disease detection using deep learning, particularly through models like Convolutional Neural Networks (CNNs), Vision Neural Networks (VNNs), and ResNet, has significantly improved the accuracy and efficiency of dermatological diagnoses. These models leverage large datasets and advanced feature extraction techniques to detect and classify skin conditions with high precision. The integration of these deep learning models into healthcare applications has led to faster diagnosis, reduced reliance on human expertise, and increased accessibility, particularly in remote areas.

However, challenges such as dataset bias, model interpretability, and regulatory compliance must be overcome for widespread clinical adoption. Despite these challenges, deep learning continues to revolutionize skin disease detection, paving the way for AI-assisted healthcare solutions that enhance early detection, improve patient outcomes, and support dermatologists in making more informed decisions. With continuous advancements, AIpowered dermatology is expected to become a vital tool in modern medical diagnostics.

The identification and management of skin diseases using convolutional neural networks (CNN) and visual geometry networks (VGG) have significantly improved the accuracy, efficiency, and accessibility of dermatological diagnosis. Traditional methods of skin disease detection often rely on manual examination by dermatologists, which can be time-consuming and prone to human error. However, deep learning models like CNN and VGG have automated the process, enabling faster and more precise classification of skin conditions. These models effectively analyze dermatological images, extract key features, and classify diseases such as melanoma, eczema, psoriasis, and nail fungus with high accuracy. By leveraging large medical datasets and transfer learning techniques, CNN and VGG models can generalize well across different skin types and conditions, making them valuable tools for computer-aided diagnosis (CAD) in dermatology.

The integration of deep learning in skin disease identification has also played a crucial role in early detection and treatment planning, reducing the risks associated with delayed diagnosis. The ability of these models to process large amounts of patient data quickly ensures that individuals receive timely recommendations for further medical consultation or treatment. Moreover, AI-powered dermatological systems are increasingly being incorporated into telemedicine applications, allowing users in remote areas to access reliable skin disease screening. Despite these advancements, challenges such as dataset biases, variations in skin tone, and model interpretability must be addressed to improve real-world applicability. Future research should focus on enhancing model robustness, increasing dataset diversity, and integrating AI-driven diagnostics with real-time clinical workflows. Overall, the use of CNN and VGG in skin disease identification and management represents a transformative shift in dermatology, making high- quality, automated, and accessible healthcare solutions a reality.

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