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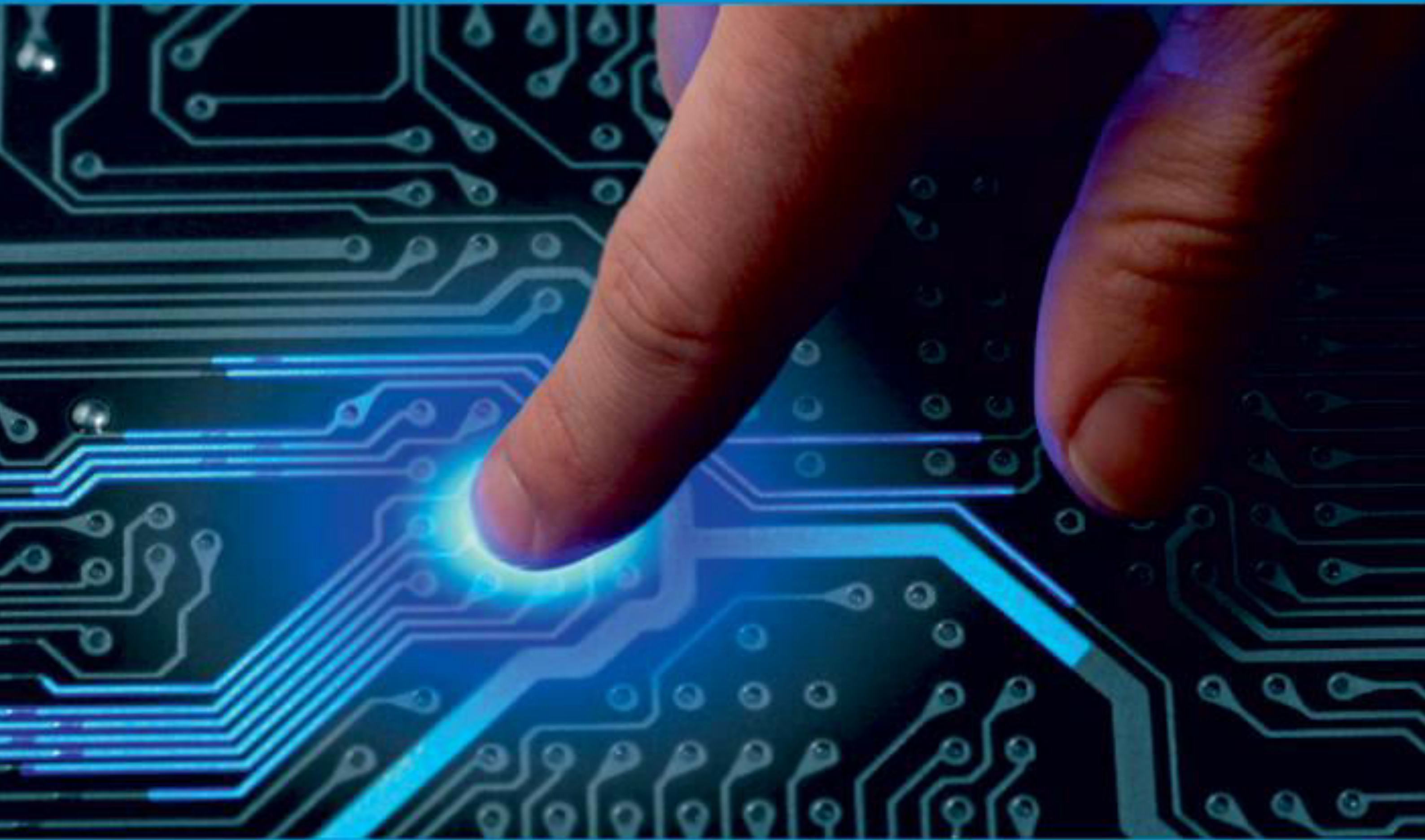

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AISkinXpert: An AI-Based Application for Early Skin Disease Diagnosis

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ABSTRACT: Skin diseases encompass a diverse range of conditions affecting millions worldwide, with early diagnosis being crucial for successful treatment and minimizing potential complications. However, traditional diagnostic processes often face obstacles like lengthy consultations and limited specialist availability, especially in remote areas. This study presents AISkinXpert, a user-centric web application employing artificial intelligence (AI) for swift skin disease diagnosis, empowering patients in their healthcare journey. The core functionality integrates deep learning models trained on a diverse dataset of dermoscopic images. Users easily upload images through a friendly interface, and the AI analyzes them, generating a detailed diagnostic report, including disease classification, a concise description, severity level, recommended remedies, and dermatologist suggestions. AISkinXpert prioritizes patient empowerment by incorporating a real-time chat feature, facilitating direct communication with recommended dermatologists for clarification and personalized advice. Users can also schedule in-person consultations with chosen dermatologists through the integrated appointment booking functionality, streamlining the transition from diagnosis to specialist care. This research showcases the feasibility and potential of AI applications in democratizing access to skin disease diagnosis and enhancing patient engagement in their healthcare journey.

KEYWORDS*:* Early diagnosis, Web Application, Deep Learning, Machine Learning, Diagnostic Report, Severity Assessment, Dermatologist Recommendations, Chat Functionality, Appointment Booking, Skin Health

I. INTRODUCTION

Skin diseases have posed an enduring challenge to human health, casting a global shadow that affects millions and presents diagnostic intricacies persisting through the centuries. Traditional diagnostic approaches, primarily reliant on visual examinations by healthcare professionals, have indeed provided valuable insights into a spectrum of conditions affecting the skin, hair, and nails. However, these approaches have grappled with inherent limitations that extend beyond the confines of mere visual scrutiny.

The historical backdrop reveals a formidable barrier to effective diagnosis – the accessibility of specialists, particularly in remote areas. The dependence on visual examinations by specialized professionals has led to potential delays in the identification and treatment of skin conditions, especially in regions geographically disadvantaged or underserved by healthcare resources. The subjectivity inherent in visual assessments introduces an element of inconsistency and delays, impacting the accuracy of diagnoses across different healthcare professionals. This scenario underscores the critical need for innovative approaches to transcend the limitations of traditional diagnostic methods.

In a quest for clarity, certain key terms crucial to this research are explicitly defined. "Skin diseases" encompass a wide array of conditions affecting the integumentary system, including the skin, hair, and nails. The emphasis on "early diagnosis" highlights the urgency of prompt and accurate identification of diseases in their initial stages, a pivotal factor for successful treatment outcomes. "Traditional diagnostic methods" encapsulate established approaches,

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predominantly visual examinations, and consultations with specialists.

Amidst the challenges posed by traditional methods, recent research has illuminated the potential of artificial intelligence (AI) to revolutionize skin disease diagnosis. These emerging AI-powered solutions offer promising avenues to address the limitations inherent in traditional approaches [1]. However, as the spotlight shifts towards AI, it becomes apparent that current tools may confront challenges related to user-friendliness, accessibility, and the comprehensiveness of the skin conditions they address.

This research, therefore, positions itself as a bridge spanning the identified gap between traditional diagnostic methods and the transformative potential of AI. At its core lies the introduction of AISkinXpert, a web application meticulously crafted to leverage the power of AI for the early diagnosis of skin diseases. The research unfolds with specific goals: the development and evaluation of AISkinXpert, a comparative analysis of its accuracy and effectiveness against traditional methods, and a comprehensive assessment of its user-friendliness and accessibility. Focused on common skin conditions, this study aims to unravel the effectiveness and user experience within a specific demographic, recognizing potential limitations and envisioning future advancements in the dynamic field of AI-powered diagnosis.

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II. LITERATURE SURVEY

Accurate diagnosis of skin diseases remains crucial for timely treatment and improved patient outcomes. Traditionally, dermatologists rely on visual examination and potentially biopsies. However, these methods can be subjective, time-consuming, and limited by access to specialists. Web-based technologies and deep learning algorithms offer promising advancements in automated skin disease detection, potentially improving accessibility, accuracy, and efficiency of diagnosis. This literature review examines recent research on web applications for skin disease detection using deep learning, exploring the potential benefits, limitations, and future directions of this technology, with a specific focus on informing the development of AISkinXpert.

i. Deep Learning for Skin Disease Detection

Several studies demonstrate the effectiveness of deep learning for skin disease classification using images [2]. [3]further explored convolutional neural networks (CNNs) for multi-class skin disease detection, achieving an accuracy of 87.4%. These studies highlight the potential of DL for accurate and automated skin disease analysis, laying the groundwork for web application development like AISkinXpert.

ii. Web Applications for Skin Disease Detection

Existing Web applications offer several advantages over mobile apps for skin disease detection. They can leverage more powerful computing resources for complex algorithms, potentially leading to improved accuracy. Additionally, web interfaces can provide a more comprehensive user experience, allowing for detailed visualizations and educational resources. However, similar to mobile apps, concerns exist regarding data privacy, security, and the potential for misdiagnosis [4]. Robust algorithms, user education, and clear disclaimers are crucial for responsible development.

iii. Challenges and Future Directions

Challenges remain in developing and deploying web applications for skin disease detection. The accuracy of DL models heavily relies on the quality and diversity of training datasets. Addressing potential biases within the data is essential to ensure generalizability across ethnicities and skin tones [5]. Furthermore, robust security measures are necessary to protect user data and comply with data privacy regulations.

In conclusion, the literature survey has illuminated the evolving landscape of skin disease detection, emphasizing the transformative potential of deep learning within web applications. The amalgamation of advanced algorithms and accessible interfaces is evident in studies by Esteva et al (2017) [2] and Yu et al. (2020) [5], provide a foundation upon which AISkinXpert can thrive. As we navigate the challenges of biased datasets, data privacy concerns, and the imperative for transparency, the outlined strategies for AISkinXpert development stand as a roadmap towards a responsible, accurate, and user-centric application.

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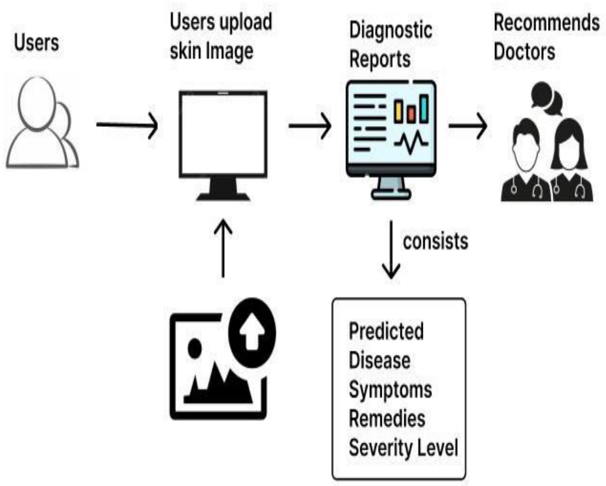
III. METHODOLOGY

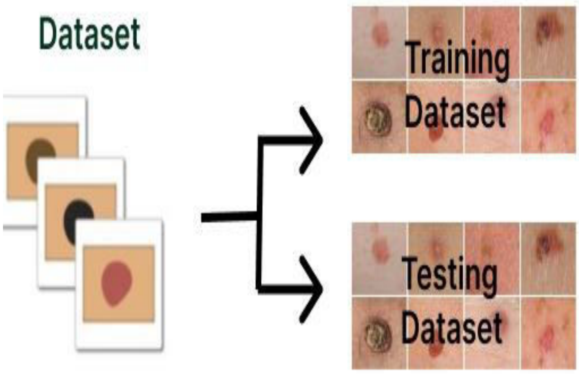
The focus of our research revolves around the development of AISkinXpert, an advanced system designed for the automated identification of various skin diseases through the application of cutting-edge deep learning techniques. The AISkinXpert system is designed to revolutionize the identification and assessment of skin diseases through a combination of deep learning techniques and user interaction. Our methodology encompasses key stages, including dataset curation, preprocessing, model architecture, and severity level assessment. A user-friendly interface allows individuals to upload skin images, answer relevant questions, and receive comprehensive diagnostic reports.

1. Key Features of AISkinXpert



2. Dataset Collection

Creating our dataset involved a careful and thorough process. We gathered data from various sources to cover a wide range of skin diseases. Important datasets like DermNet and SkinDataset were particularly helpful, providing us with diverse and extensive collections for our training and testing sets. These datasets form the backbone of our model training, ensuring it learns from a rich variety of skin conditions. The training dataset comprises a substantial collection of 15,500 images, carefully annotated to cover 23 distinct skin diseases. To validate the robustness of our model, a separate test set consisting of 4000 images was curated. This dataset includes challenging cases, ensuring the model's proficiency in handling various skin conditions. Each image was thoroughly annotated to provide the necessary ground truth for the training and testing phases.



3. Data Preprocessing

Before training, the collected images underwent rigorous preprocessing steps to standardize resolution, ensure consistency, and address any potential biases. This preprocessing phase aimed to enhance the generalization capabilities of our model and mitigate the impact of variations in image quality.

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4. Deep Learning Models Selection

ResNet50, VGG19, and Xception are well-established convolutional neural network (CNN) architectures frequently employed in computer vision tasks. ResNet50, a variant of ResNet, is renowned for its success in addressing the vanishing gradient problem through the use of residual connections. VGG19, characterized by its simplicity and uniform architecture, and Xception, employing depthwise separable convolutions, also demonstrate competitive performance.

4.1 Xception Architecture

The Xception model, developed by [6], is a highly efficient deep convolutional neural network architecture renowned for its outstanding performance in image classification tasks. Its unique design, featuring extreme depth, makes it a notable choice in computer vision applications, particularly for image recognition and feature extraction.

Scientists and researchers leverage the Xception model across various domains due to its intricate architecture. The model begins with an input layer configured for processing 224x224 pixel images with three RGB color channels. Unfolding through 36 feature extraction blocks, labeled block1 to block14, the model employs separable convolution layers for efficient feature extraction, enabling it to discern intricate patterns in the data.

A crucial transition occurs with the Global Average Pooling layer, strategically placed to condense the tensor's spatial dimensions into a concise 1x1 feature vector. This transformation sets the stage for fully connected layers, enriched with dense connections and fortified by batch normalization. At the heart of the classification task, the final dense layer produces an output shape of (None, 3), highlighting the model's proficiency in handling three distinct classes.

The architectural magnificence of Xception extends to its parameter configuration, totaling 22,053,931 parameters. Of these, 1,186,819 are trainable, while 20,867,112 remain non-trainable, with their weights deliberately frozen during training. This nuanced interplay of architecture and parameters equips the Xception model to navigate the complexities of diverse datasets, establishing it as a cornerstone in the domain of image classification and feature extraction.

4.2 VGG19 Architecture:

VGG19, a variant of the VGG (Visual Geometry Group) architecture, is a deep convolutional neural network designed for image classification. It was introduced by Karen Simonyan and Andrew Zisserman in their 2014 paper "Very Deep Convolutional Networks for Large-Scale Image Recognition. [6] ". VGG19 is renowned for its simplicity and uniform architecture, consisting of multiple convolutional and pooling layers.

VGG19 is composed of 16 convolutional layers, grouped into five convolutional blocks, followed by three fully connected layers. The convolutional blocks are labeled as "block1" through "block5." Each block consists of multiple convolutional layers, followed by a max-pooling layer to reduce spatial dimensions.

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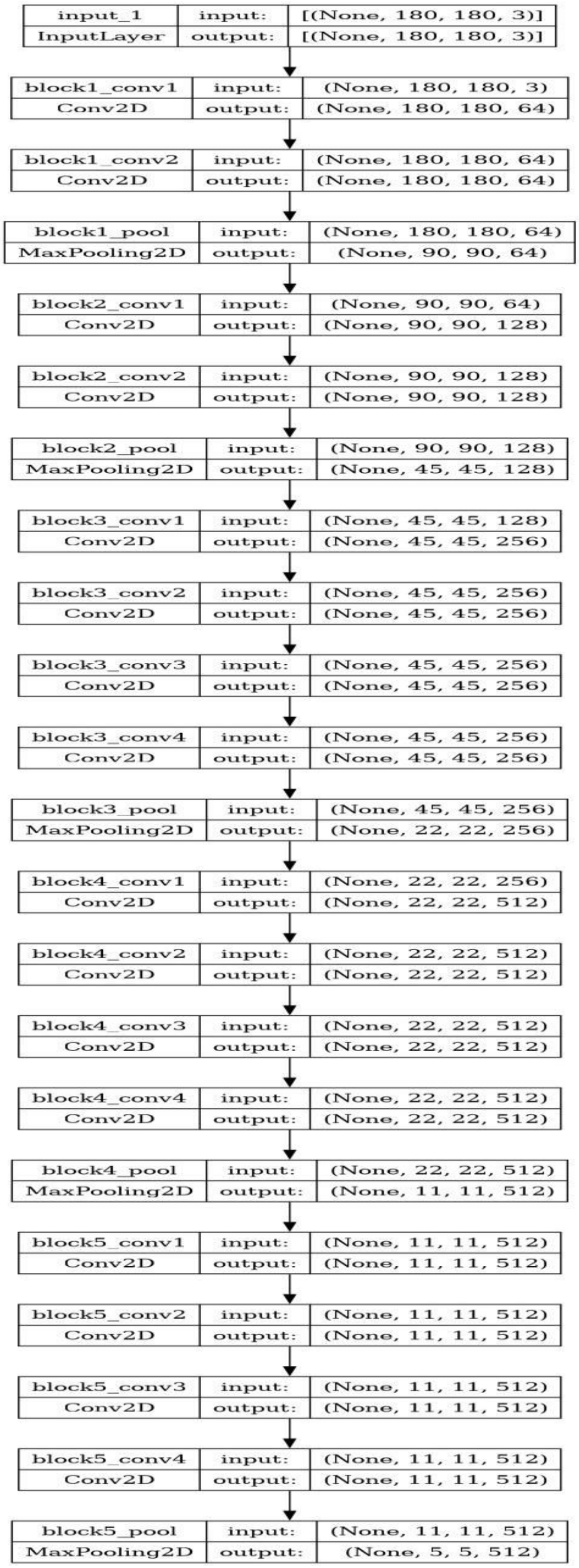

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4.3 ResNet50 Architecture:

ResNet50, a groundbreaking deep learning architecture, was introduced by in their 2016 paper titled "Deep Residual Learning for Image Recognition. [7]". This architecture addresses challenges associated with training very deep neural networks, such as the vanishing gradient and degradation problems. As neural networks grow deeper, issues arise, including the vanishing gradient problem and the degradation problem, where adding more layers unexpectedly increases training error. Traditional networks become challenging to optimize and train as their depth increases.

ResNet50, which stands for Residual Network with 50 layers, represents a pivotal solution to the vanishing gradient problem. It introduces residual connections, allowing the network to learn residual functions instead of directly learning desired mappings. This innovation facilitates the training of exceptionally deep networks, making ResNet50 well-suited for complex image recognition tasks. ResNet50 has demonstrated remarkable performance in various computer vision benchmarks and competitions, becoming widely adopted in deep learning applications.

This powerful deep-learning model features 24 layers and is commonly used for image classification tasks. The architecture utilizes residual blocks for effective training, beginning with a standard convolutional layer followed by batch normalization and rectified linear unit (ReLU) activation. Max pooling is employed for spatial dimension downsampling, enhancing the model's ability to capture hierarchical features.

ResNet50's key innovation lies in its use of shortcut connections, or skip connections, within residual blocks. These connections facilitate the flow of information through the network by bypassing certain layers, mitigating the vanishing gradient problem and enabling the training of very deep networks.

As the network progresses, spatial dimensions decrease, and the number of filters increases, capturing increasingly abstract and high-level features. The model incorporates global average pooling to aggregate spatial information, reducing parameters before transitioning to dense layers for classification.

The architecture concludes with two fully connected layers – the first with 512 units and ReLU activation, and the second with 23 units, corresponding to the number of output classes. ResNet50 boasts a substantial parameter count of 24,648,599, with 1,060,887 trainable parameters, showcasing efficiency in training. The non-trainable parameters primarily consist of skip connections, crucial for capturing intricate features and patterns, making ResNet50 a prominent choice in various computer vision applications, including AISkinXpert.
In our study, we rigorously evaluated three prominent deep learning models—Xception, VGG19, and ResNet50—each pre-trained on extensive image datasets. The primary objective was to discern the model that best suited our image classification task. These models underwent comprehensive training, fine-tuning their pre-trained weights on our dataset and incorporating data augmentation techniques to enhance generalization capabilities. Extensive hyperparameter tuning was conducted, optimizing parameters such as learning rates and batch sizes for optimal performance. Following a robust validation process on a separate dataset, the ResNet50 model consistently demonstrated superior accuracy, achieving an impressive 92%. Thus, based on empirical evidence, we selected ResNet50 as the most effective architecture for our specific dataset and classification task.

5. Severity Level Calculation

In our methodology, we designed a straightforward and user-friendly approach to determine the severity level of skin conditions, specifically Actinic Keratosis (AK). Recognizing the absence of a universal severity formula, we adopted the Actinic Keratosis Area and Severity Index (AKASI), a proven method primarily applied to monitor treatment outcomes, especially in cancer cases [8]. To gauge the severity, we considered key parameters such as age, gender, redness, thickness of the disease, duration of the disease, and Body Mass Index (BMI). The user is prompted with a set of questions addressing these factors to ensure a comprehensive evaluation. For BMI calculation we used this formula,

BMI = Weight (in Kg) / ((Height (in m))2**

The severity level is then calculated using the AKASI score, which involves assessing solar damage (SD), distribution of AK (D), erythema of AK (E), and thickness of AK (T) across different facial regions. The AKASI score is determined for each area (scalp, forehead, right face, left face) and aggregated, considering the weighted contribution of each region to the overall severity. The formula for calculating the AKASI score is as follows:

AKASI Score =0.4×(D+E+T+SD of Scalp)+0.2×(D+E+T+SD of Forehead)+0.2×(D+E+T+SD of Right Face)+0.2×(D+E+T+SD of Left Face)

The research categorized AKASI scores as follows: below 2.9 - mild, 2.9 to 5.3 - moderate, 5.3 to 8.3 - severe, and above 8.3 - very severe.

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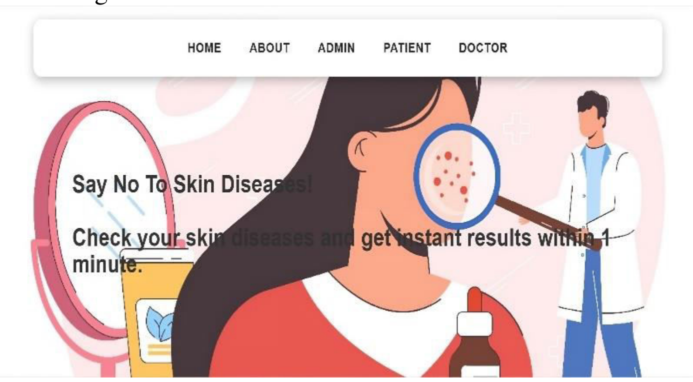
A total of 23 skin diseases were meticulously classified and documented to ensure a comprehensive representation of dermatological conditions.

III. RESULTS AND DISCUSSIONS

Our evaluation of AISkinXpert, a web application for skin disease diagnosis using deep learning, yielded promising results. The ResNet50 deep learning model achieved an impressive 92% accuracy in classifying various skin diseases from user-uploaded images on a large test dataset. This showcases its potential to effectively analyze images and identify a wide range of skin conditions. Additionally, the user-friendly approach for calculating AK severity using the AKASI score provided valuable insights for Actinic Keratosis cases.



This is our AISkinXpert Home page

Name	Email	Gender	Age	Phone Number	Experience	Hospital Name	Address	Appointment	Let's Chat
Doctor	docto@gmail.com	Male	45	9632587410	Senior Doctor(10+ years of experience)	Manipal Hospital	Bangalore	Book	Chat
doctorh	hello@gmail.com	Female	23	9632587410	Junior Doctor(0-3 years of experience)	Max Super Speciality Hospital	Delhi	Book	Chat

[9]

Figure 2 showcases a sample diagnostic report generated by AISkinXpert. It presents the identified disease name, a brief description of its severity level, and recommended remedies. Additionally, the report offers a valuable feature: the ability to connect with qualified dermatologists via a chat function and schedule appointments directly within the application.

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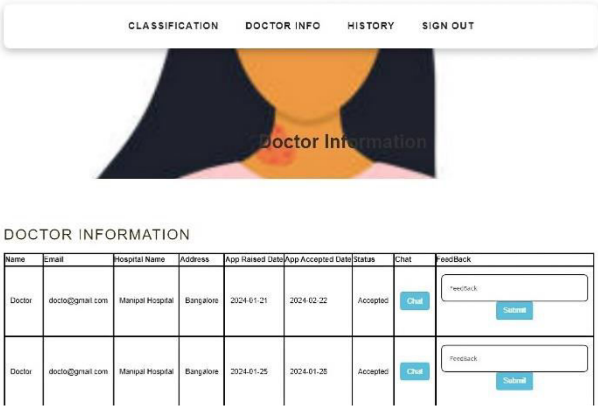

However, there's room for improvement. The current version focuses on a specific set of conditions. Expanding the model's capabilities to encompass a broader range of skin conditions and integrating additional metrics for severity assessment beyond AKASI would enhance its versatility. Future work will also address ethical considerations and transparency. The application will communicate that it serves as a diagnostic aid and not a replacement for consulting a dermatologist.

Overall, the high accuracy of the deep learning model and the user-friendly interface position AISkinXpert as a valuable tool with the potential to empower individuals, improve healthcare outcomes, and contribute to earlier skin disease detection.

IV. CONCLUSION

AISkinXpert, a web application for skin disease diagnosis using deep learning, achieved a high accuracy of 92% in classifying various skin conditions. This user-centric approach, coupled with the user-friendly interface and AKASI score-based severity assessment, empowers individuals for early detection. While future work will address expanding the range of conditions and incorporating additional metrics, AISkinXpert presents a promising step towards democratizing access to skin disease diagnosis and improving health outcomes.

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