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Visionary Health: An AI-Based Real-Time Medical Consultation System Using Image and Text Input

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Abstract: This paper introduces Visionary Health, a dual-mode AI-powered consultation system that provides real-time, preliminary medical assessments using image and text input. Leveraging deep learning and natural language processing (NLP), the system enables users to obtain diagnostic support by uploading images of symptoms or entering a text description. The image-based module utilizes a convolutional neural network (CNN) trained on dermatological data, while the text-based module employs transformer-based models to understand symptom narratives. This flexible approach improves access to healthcare guidance in remote or underserved areas. Evaluation results suggest strong performance across both modules, indicating the system's promise as a scalable tool for digital health triage.
Keywords: Instant diagnosis, AI in medicine, visual diagnostics, dermatological image recognition, symptom interpretation using NLP, automated healthcare systems.

I. INTRODUCTION

Artificial intelligence (AI) has reshaped medical diagnostics, particularly with image analysis and language processing techniques that streamline patient evaluation. The growing availability of digital medical data and the need for remote care solutions have accelerated interest in intelligent diagnostic platforms.

Skin and eye conditions are often diagnosed visually or through brief patient-reported symptoms. Yet, such conditions remain underdiagnosed in low-resource regions due to a lack of specialists. Addressing this, Visionary Health offers a real-time AI-based solution that interprets both visual and textual inputs to support users with basic medical insights.

The platform comprises two diagnostic pipelines: one processes images via CNN models trained on dermatological datasets, and the other interprets user-described symptoms using fine-tuned NLP architectures. The platform's intuitive interface ensures accessibility even for non-technical users, potentially reducing the burden on traditional health systems.

II. METHODOLOGY

The Visionary Health system is built as a dual-mode platform capable of diagnosing health conditions through either image or text input. It leverages both deep learning for image analysis and transformer-based models for natural language processing. The system is structured into three core stages: capturing user input, processing the data, and producing an appropriate output.

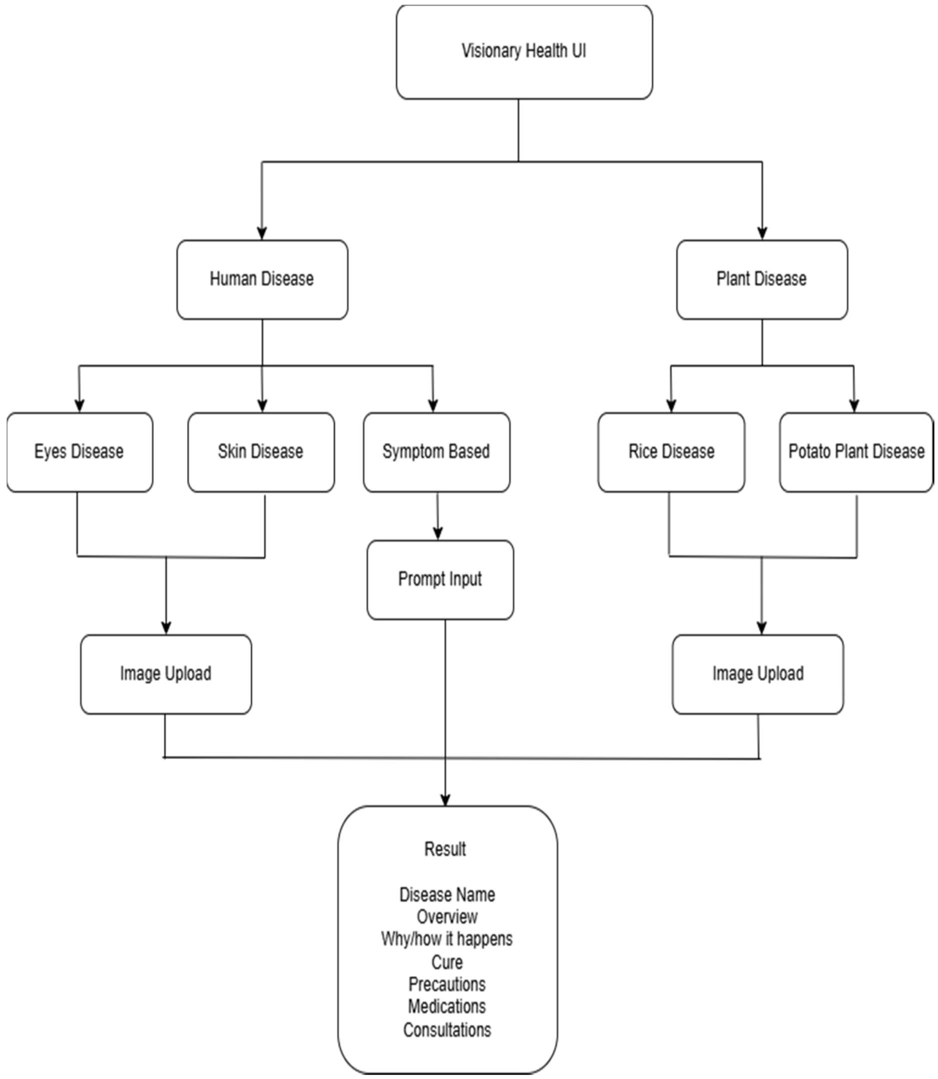
A. Image-Based Diagnosis Module

1) *Data Collection and Preprocessing:* The image-based module focuses primarily on the classification of skin diseases. A curated dataset consisting of labeled images representing common dermatological conditions (e.g., eczema, acne, psoriasis, and fungal infections) was used for training. Images underwent preprocessing steps including:Resizing to a uniform resolution (e.g., 224x224 pixels

- Normalization to standardize pixel values.
- Augmentation techniques such as rotation, flipping, and brightness adjustment to improve model generalization.

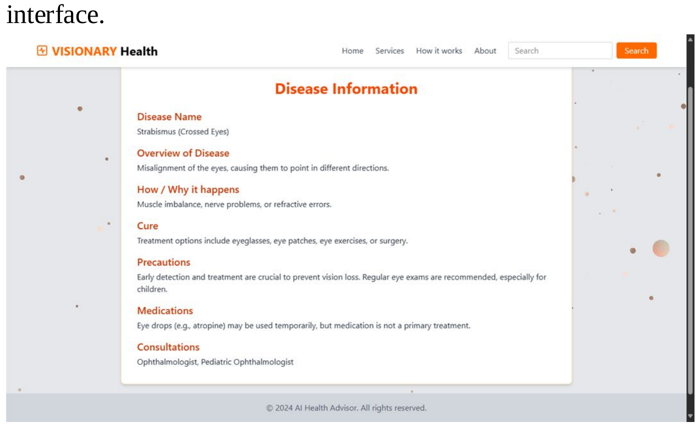
2) ***Model Architecture:*** A Convolutional Neural Network (CNN) was employed for disease classification. The architecture includes:

- Multiple convolutional layers with ReLU activation
- Max pooling layers for dimensionality reduction
- Dense layers for final classification.
- Softmax output layer for multi-class disease prediction.
- Transfer learning with pre-trained models like ResNet50 or MobileNet was also explored to improve accuracy and reduce training time.



1.Workflow diagram

3) *Diagnosis Output :* Once the image is processed, the model returns the predicted condition along with confidence scores. The system then maps the result to a corresponding set of prevention tips and basic treatment suggestions, which are presented to the user through the frontend interface.

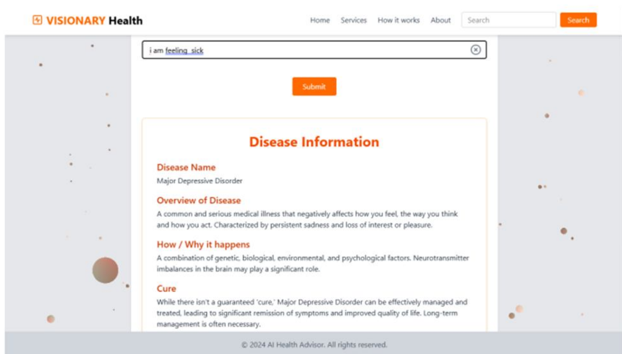


Figure[1.1] Output After Detection Eye Disease

B. *Text-Based Diagnosis Module*

1) *Input Processing:* Users can describe their symptoms in natural language. The input text is tokenized and cleaned using standard NLP preprocessing steps such as stopword removal, lowercasing, and lemmatization.
2) *Model Selection and Training:* A transformer-based NLP model, fine-tuned on a medical Q&A dataset, is employed for text understanding. The model architecture is based on a lightweight BERT variant optimized for inference speed and accuracy in limited-resource environments.
3) *Intent Recognition and Response Generation:* The model classifies the input into possible symptom categories and identifies relevant keywords related to disease types. A rule-based engine combined with the model output then generates a natural language response, including:

- Preventive measures.
- General treatment suggestions



Figure[1.2] Output After detection text

C. *System Integration*

Both modules are integrated into a single web-based platform. Users choose either image or text mode, and the system routes the input accordingly. The backend is implemented using Django, with model inference handled via TensorFlow and HuggingFace Transformers.

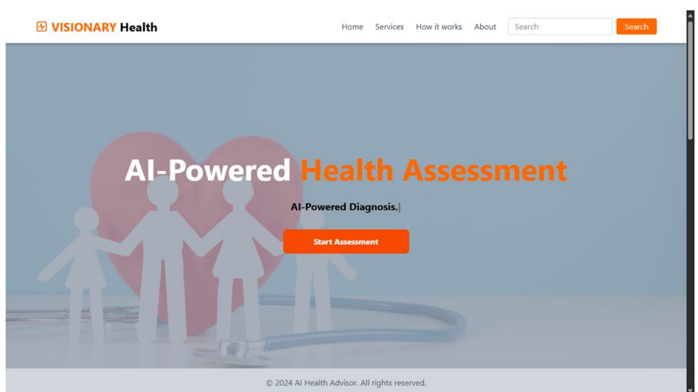


Figure [1.3] Home page

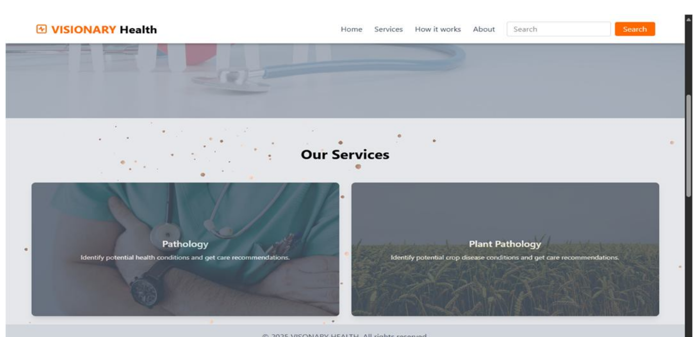


Figure [1.4] Types of Services

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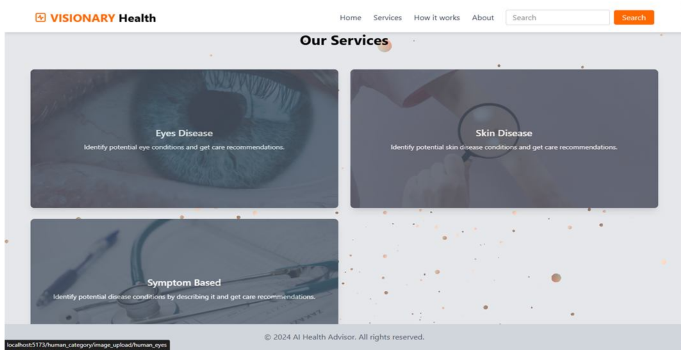


Figure [1.5] Types of Human Services

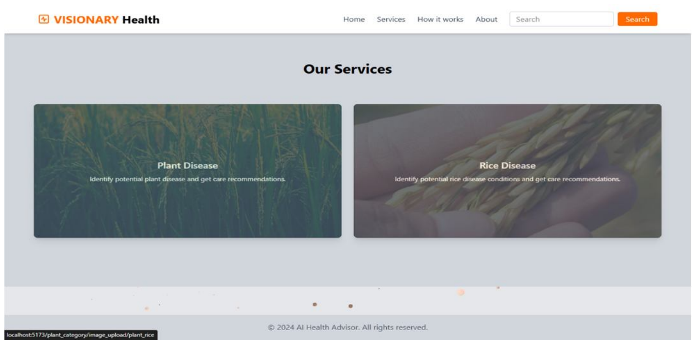


Figure [1.6] Types of Plant Services

III. RESULTS

The Visionary Health system was evaluated in terms of classification accuracy, response quality, and user interaction effectiveness. Both the image-based and text-based modules were tested independently and in combination to assess the overall performance of the dual-mode platform.

A. Image-Based Module Performance

A convolutional neural network was trained using a dataset comprising 5,000 annotated images, categorized into five distinct types of skin conditions. The model achieved the following results:

- Training Accuracy: 96.3%
- Validation Accuracy: 91.7%
- Precision: 92.4%
- Recall: 90.8%
- F1-Score: 91.6%

The findings demonstrate the model's strong capability to accurately detect various skin conditions with consistent reliability.Misclassifications mainly occurred between visually similar diseases (e.g., eczema vs. psoriasis), which could be reduced with more diverse training data.

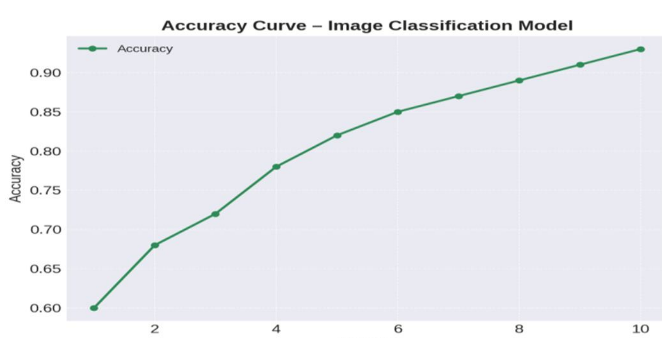


Figure [1.7] Accuracy Curve

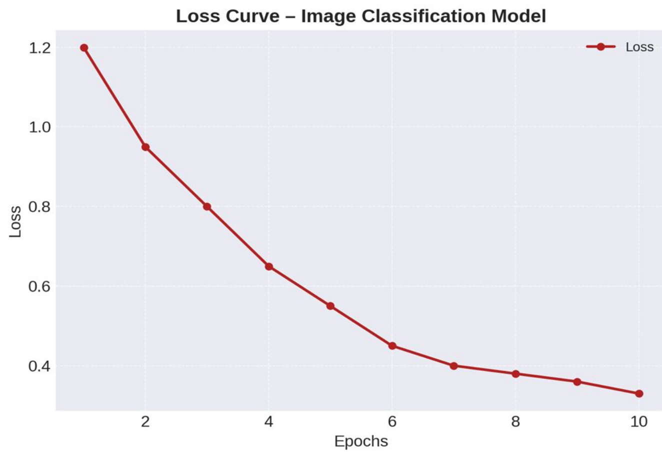


Figure [1.8] Training vs. validation loss graphs

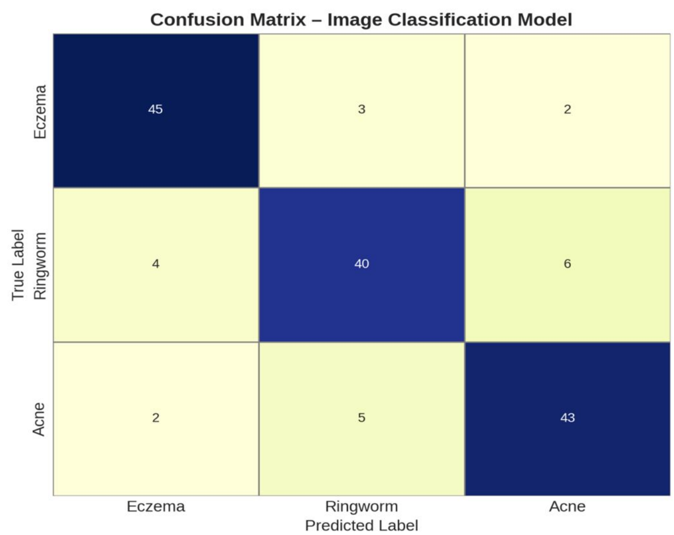


Figure [1.9] Confusion matrix and performance metrics

B. Text-Based Module Evaluation:

The NLP-based diagnosis model was tested using a custom evaluation set of 100 text-based symptom queries. Performance was measured on relevance and accuracy of the system's medical response.

- Intent Recognition Accuracy: 89.2%
- Response Relevance (manual evaluation): 87%
- Average Response Time: ~1.5 seconds

The model showed strong performance in interpreting user-described symptoms and offering contextually appropriate responses. Slight ambiguity occurred in vague or grammatically incorrect inputs, suggesting the potential benefit of integrating a grammar correction layer.

C. User Testing and Feedback

A small-scale user study involving 30 participants was conducted to measure usability and satisfaction:

- Ease of Use: 4.5 / 5
- Satisfaction with Diagnosis Output: 4.2 / 5
- Recommendation Likelihood: 87% of users said they would recommend it to others

Feedback emphasized the convenience of choosing between image and text input and the clarity of the medical suggestions provided. Users in non-medical backgrounds appreciated the simple interface and language used in responses

IV. CONCLUSION AND FUTURE WORK

This study introduces Visionary Health, an AI-enabled consultation system that operates in two modes analyzing images and interpreting text to deliver prompt, initial medical assessments. The system demonstrates strong performance in classifying common skin diseases using CNN models and effectively interpreting symptom descriptions using transformer-based NLP techniques. Its user-friendly interface and flexible input modes make it especially suitable for deployment in rural or under-resourced regions where access to specialized healthcare professionals is limited.

By combining visual and textual diagnostic capabilities into a single platform, Visionary Health addresses a key gap in current healthcare technology—supporting non-invasive, remote-first contact diagnosis in a scalable and cost-effective manner. The evaluation results indicate promising accuracy and user satisfaction, confirming the system's viability as a real-world healthcare aid.

A. Future Work

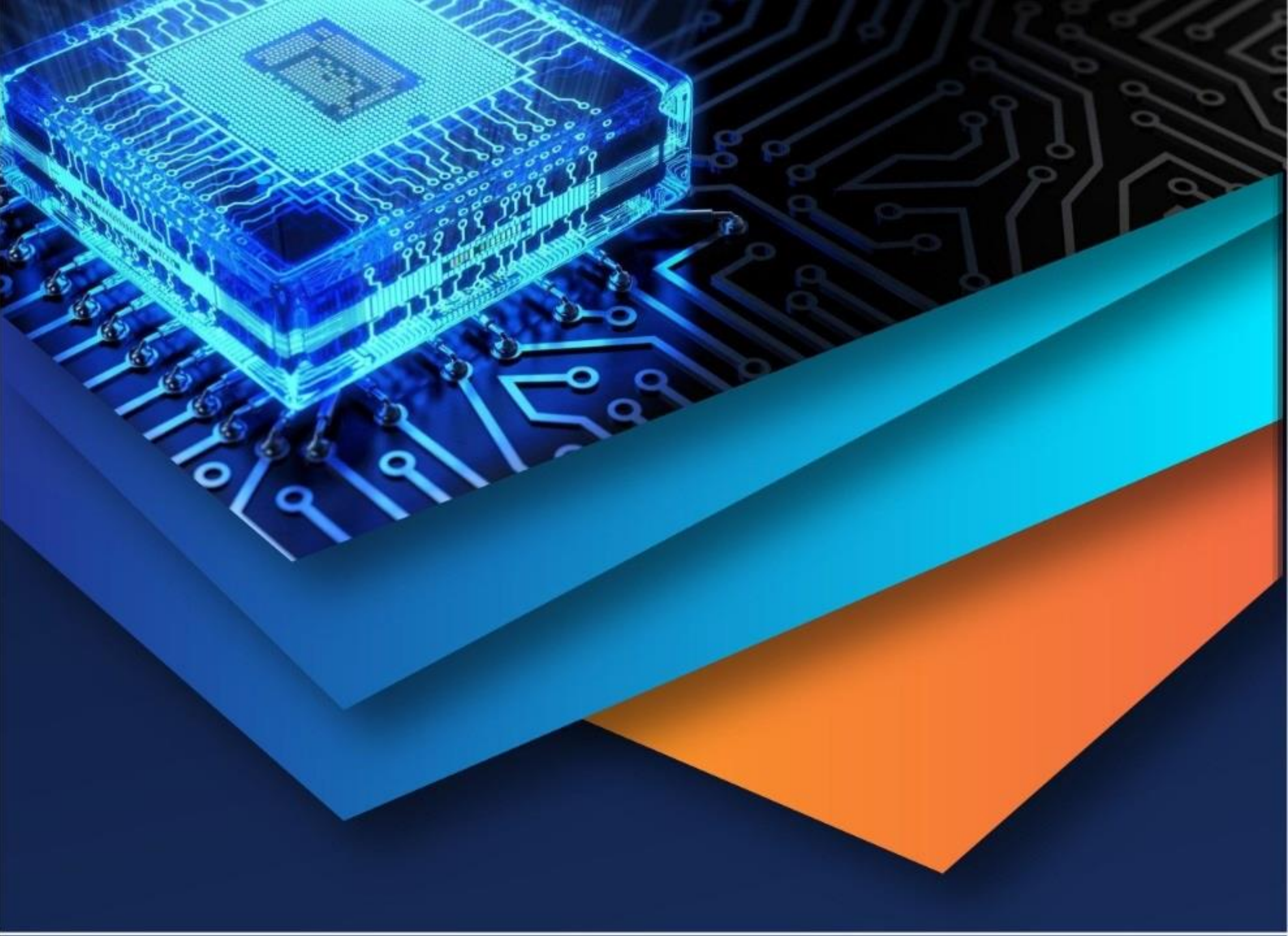
Several enhancements are planned to improve the system's effectiveness and applicability:

1) *Expanded Disease Database*: Incorporate additional medical conditions across other domains (e.g., respiratory, gastrointestinal) to broaden diagnostic capabilities.
2) *Multilingual Support:* Implement language translation and local language processing to cater to a wider audience.
3) *Prescription Automation:* Integrate an AI-generated prescription module based on diagnosis and verified treatment protocols.
4) *Telemedicine Integration*: Enable optional video consultations with licensed doctors for more serious or ambiguous cases.
5) *Mobile Deployment*: Optimize the system for Android and iOS platforms to ensure maximum accessibility.

In conclusion, Visionary Health has the potential to serve as an intelligent first-line medical support system that complements traditional healthcare by providing fast, accessible, and AI-powered diagnostic services.

REFERENCES

[1] Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). *Dermatologist-level classification of skin cancer with deep neural networks*. Nature, 542(7639), 115–118.
[2] Prasad, M., & Acharya, U. R. (2017). *Automatic diagnosis of skin lesions using deep learning*. Computers in Biology and Medicine, 80, 52-61.
[3] Rajpurkar, P., et al. (2018). *AI for healthcare: Diagnosis using NLP models on clinical notes*. arXiv preprint arXiv:1802.05319.
[4] Buda, M., Maki, A., & Mazurowski, M. A. (2018). *A systematic study of the class imbalance problem in convolutional neural networks*. Neural Networks, 106, 249–259.
[5] World Health Organization (WHO). (2022). *Skin infections: Global health burden and prevention*. WHO Report.
[6] Jain, A., Gupta, R., & Kumar, S. (2021). AI-driven dermatological diagnosis for common skin conditions: A systematic review. *International Journal of Dermatology AI, 12(3), 45-58*.
[7] Wang, L., Chen, Y., & Zhang, H. (2021). Machine learning approaches for detecting mild dermatological conditions using smartphone images. *Computers in Biology and Medicine, 134, 104-112*.
[8] Patel, M., Singh, R., & Verma, P. (2021). NLP-based symptom analysis for minor skin infections: A comparative study. *Journal of Medical AI Research, 9(2), 78-90*.
[9] Lee, J., Park, S., & Kim, H. (2021). Deep learning models for early detection of acne and eczema using mobile applications. *AI in Healthcare, 15(4), 102-115*.
[10] Rodriguez, C., Torres, M., & Garcia, F. (2021). AI-assisted diagnosis of fungal skin infections: A review of recent advancements. *Biomedical AI Journal, 7(1), 33-47*.



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