iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: III Month of publication: March 2026

DOI: https://doi.org/10.22214/ijraset.2026.79176

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

Lesion Interpretation System Using Image Processing

H Meenal[1], V Swapnika[2], M Partha Saradhi[3], S Vinay[4]
[1]Department of Computer Science and Engineering, Methodist College of Engineering and Technology Abids, Hyderabad, Telangana, 500001, India
[1,2,3,4]Department of Artificial Intelligence and Data Science, Methodist College of Engineering and Technology Abids, Hyderabad, Telangana, 500001, India

Abstract: This Due to the significant visual similarities between different lesion pattern types and the inconsistent quality of photographs taken in real-world settings, accurately identifying dermatological abnormalities continues to be a significant difficulty. Automated preliminary assessment is becoming more important due to the growing requirement for intelligent support systems that are both efficient and effective. The framework for an integrated method of analyzing and interpreting lesion images using deep learning and image processing is put forward. To enhance the quality and consistency of the analysis, the input image undergoes preprocessing steps such illumination evaluation, scaling, and normalizing. A convolutional neural network is then employed to obtain complex representations and classify the images for various lesion types. The interpretation ability of the output results is enhanced by incorporating an interpretation layer to provide descriptive results and precautionary advice. In addition, a threshold-based segmentation approach is employed to determine the spread of the lesion, thereby allowing for an indication of the severity in a simplified manner. The suggested strategy shows the potential for an efficient and successful support system for early-stage.
Keywords: Convolutional Neural Network, Dermatological Analysis, Image Normalization, Image Preprocessing, Lesion Interpretation, Medical Image Analysis.

I. INTRODUCTION

The domain of medical image analysis has witnessed tremendous changes during the past three decades with the advent of various computational and data-oriented approaches. Initially, the systems were mainly dependent upon traditional image processing techniques such as edge detection, region-based image segmentation, and geometric modelling. These techniques were usually implemented by a rule-based approach in which the decisions were made by applying a set of predefined rules. Although the systems were successful in a controlled environment, they were not flexible and failed to cope with the uncertainties present in real-world images [8],[9].

With the development of machine learning, data-centric methods gained prominence, allowing machines to directly learn discriminative patterns from images. Although techniques based on statistical classification and feature extraction enhanced diagnostic accuracy, their reliance on features limited their capacity to handle complex visual differences under various imaging settings [6],[11].

The application of deep learning methods, particularly convolutional neural networks (CNNs), in learning feature pattern hierarchies was a notable milestone in this field. Substantial breakthroughs in computer vision have been achieved with the success of deep learning methods, such as AlexNet, in large-scale visual recognition tasks [3],[10]. As a result of their potential in learning complex patterns and textures, CNN and hybrid models are conclusively established to be the most efficient in medical image analysis [19],[21].

Despite these advances, there are some challenges associated with dermatological image analysis. The main challenges are the high similarity between various dermatological lesion classes, which makes the classification process challenging. In addition, there are concerns regarding illumination and device quality, which affect the performance of the system [7],[20]. Moreover, most dermatological image analysis systems are designed for classification purposes and do not consider interpretability, relevance, and usability [24],[25]. In order to overcome the limitations of the aforementioned approaches, a hybrid analytical approach that combines im-age processing and deep learning is proposed. The approach includes image preprocessing techniques such as image quality assessment, normalization, and resizing to improve the robustness of the input image under different environmental conditions [2],[5].

A convolutional neural network is utilized for multi-class classification to effectively recognize the features of different types of lesions. In addition to classification, an interpretation component is integrated, which associates predictions with relevant information such as symptoms and safety information. Moreover, an estimate of the extent of lesion spread can be obtained based on a threshold-based approach.

This provides an additional measure of severity without requiring computationally expensive segmentation approaches. In addition to classification, an interpretation component is integrated, which associates predictions with relevant information such as symptoms and safety information. Moreover, an estimate of the extent of lesion spread can be obtained based on a threshold-based approach. This provides an additional measure of severity without requiring computationally expensive segmentation approaches.

II. LITERATURE REVIEW

Significant progress in the field of medical image analysis has led to the development of complex models for the interpretation of the image in terms of lesions, with emphasis on practical applications. A lot of research work has gone into the development of models that are not only compact and resource-friendly for practical applications on mobile and edge platforms but also provide the capability for efficient performance with acceptable levels of accuracy [1],[4],[18],[26]. However, the emphasis in these models is on efficiency and not interpretability and does not provide the capability for obtaining information. In order to further enhance classification performance in var-ying imaging conditions, hybrid models along with transformer-based architectures have been extensively explored. By integrating CNN-based models along with attention-based mechanisms or lightweight vision transformers, recognition accuracy has been significantly enhanced in terms of recognizing local textures as well as global contextual information [3],[17],[21].

Even though such models have been found to enhance recognition accuracy, their computational complexity remains relatively high. Segmentation-based methods have also achieved prominence in recent times due to their ability to assist in the localization of regions of interest along with the elimination of background noise. Various research works have been performed to facilitate the improvement of boundary localization along with the elimination of artifacts from non-dermoscopic images. Some of the methods include the use of lightweight segmentation networks and attention-based refinement methods, etc. [8,][9],[12],[23]. Although the use of segmentation-based methods facilitates the localization process, complexity is introduced.

Apart from classification and segmentation, recent studies have also focused on severity estimation to provide more analytical insights into the data. Regression-based models have been used to measure the progression of lesions and provide continuous severity scores [13]. These approaches, although more clinically relevant, are highly dependent on the availability of annotated data and are also prone to subjectivity.

The importance of these preprocessing strategies can be gauged from the fact that these preprocessing strategies contribute to the robustness of these systems, especially in handling varying lighting conditions, camera quality, and skin tones. Various preprocessing strategies are employed to normalize the input images and make them more consistent with varying scenarios [2],[5],[12],[20]. However, as indicated in the literature, even these preprocessing strategies are faced with the challenge of handling the intricacies of real-world variations. Fairness, Generalization, and Reliability are identified as key challenges in recent literature. Various pieces of literature have indicated that the varying distribution and lack of representation of diverse skin tones may impact the performance of the system [11],[14].

In this regard, various strategies of confidence calibration are employed to improve the reliability and overcome the overconfidence of these systems [24],[25]. Overall, the existing methods have shown that there has been a significant improvement in the classification, segmentation, and interpretation of lesions with the help of lesion classification systems. However, the systems still require more efficient solutions in terms of high computational costs, lack of real-time processing, lack of preprocessing, and lack of decision support systems in the systems.

III. PROPOSED FRAMEWORK

Deep learning, image processing, and decision support systems will all be integrated into this system. The interpretation of the lesions in a practical setting will benefit from this. The basic picture acquisition, processing, classification, and output creation processes form the foundation of this system. By incorporating light image processing and a deep learning model, this system will be more effective than existing systems that use image segmentation algorithms. The addition of clinical information and lesion severity will make this method easier to understand.

A. System Architecture

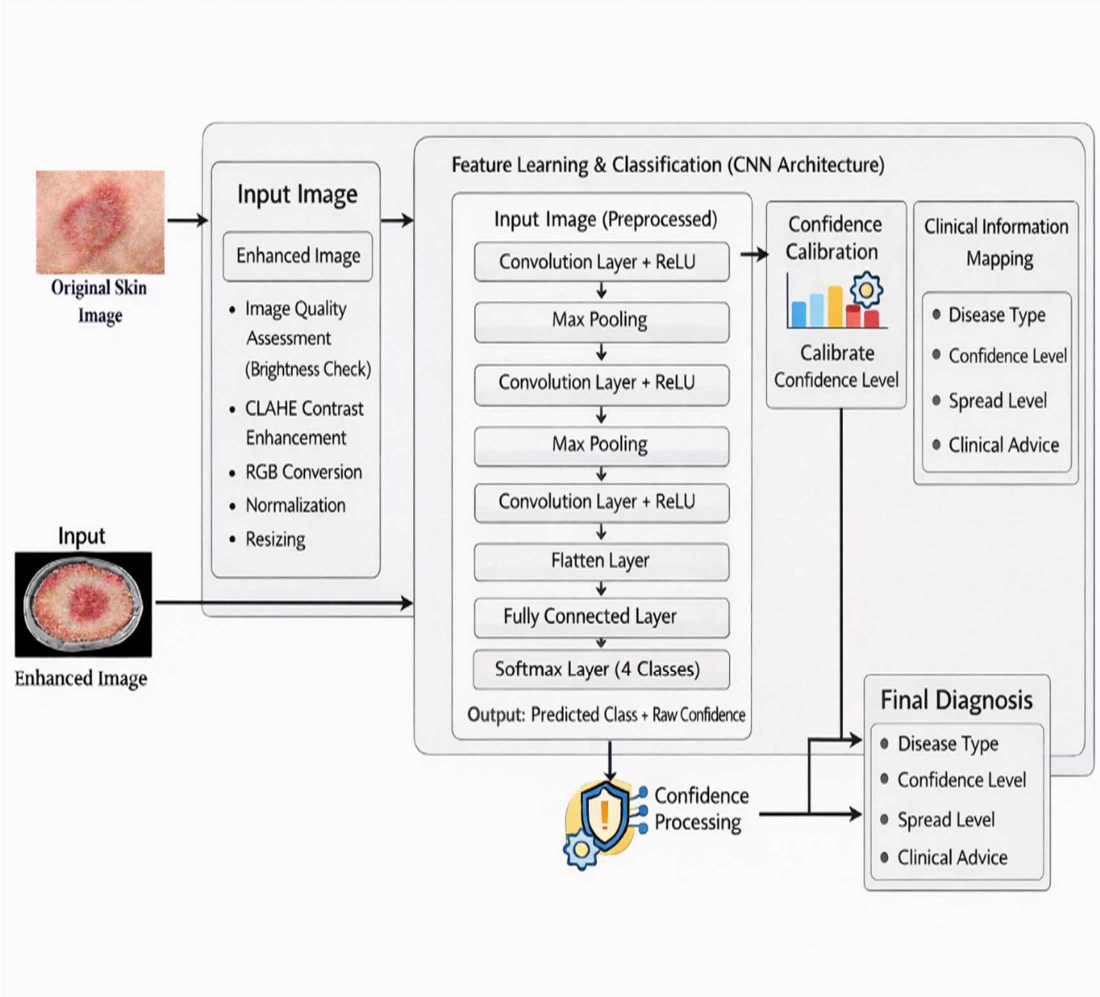

Fig. 1 System Architecture of Lesion Interpretation System

The Fig. 1 System Architecture of Lesion Interpretation System indicates a pattern of a sequential image processing pipeline, which transforms an unprocessed image to a meaningful image. The image preprocessing, which normalizes the image, occurs after the image has been acquired through the user interface. This image then goes through the deep learning algorithm for classification. The confidence calibration has been included in this system to make it more efficient. Also, the estimation module has been included to find out how much area needs to be calculated. In order to complete the image for preliminary analysis, clinical knowledge has been included.

B. Image Preparation and Enhancement

Every For this purpose, to maintain consistency in terms of the in-put, some preprocessing steps are taken. The image uploaded by the user is checked for image quality through brightness analysis. Then, the image is resized to a size of 224x224 pixels, converted to RGB mode, and normalized to the range [0, 1]. This reduces the effect of lighting conditions and image acquisition devices used to capture images [2],[5].A simple threshold-based technique is used to identify regions affected, in order to estimate the spread of lesions based on intensity variation.

C. Deep Learning Classification Model

The framework utilizes a convolutional neural network to carry out multi-class classification. The network examines the input image to extract the relevant features and provides probability estimates for the classes. The output is deter-mined based on the class with the highest probability, enabling effective discrimination between various types of lesions [19],[21].

D. Pseudo Code of Lesion Interpretation System

```
Input: Skin Image (I)
Output: Class, Confidence, Quality, Spread, Advice
1. Read image I
Begin

2. Quality Check
   B <- mean(I)
   if B not in range
    Quality <- "Sub-optimal"
   else
     Quality <- "Optimal"
3. Preprocess
   Resize to (224x224)
   RGB
   Normalize: I <- I / 255

4. Prediction
   P <- model(I)
   Class <- argmax(P)
   Confidence <- max(P)

5. Spread Analysis
   G <- grayscale(I)
   Threshold
   Spread <- (lesion_pixels / total_pixels) * 100

6. Clinical Mapping
   Symptoms and Advice for Class

7. Return output
End
```

IV. RESULTS AND DISCUSSIONS

The end-to-end functionality of the proposed AI-based skin lesion analysis system is represented through figures. Fig. 2 Home Page Interface represents the homepage interface, which is important from the perspective of ensuring the usability of the system. The homepage is represented as an interface where users can easily upload the images as well as explore the various skin lesion conditions.

The functionality of the system is represented through Fig. 3 Internal System Working, where the system processes the input image through the deep learning-based system to ensure the classification, quality assessment, as well as the spread evaluation. Fig. 4 System Analysing the Lesion represents the functionality of the system in terms of the analysis provided to the user, where the system not only classifies the condition with the confidence score but also offers various forms of additional information such as the quality assessment, symptom assessment, as well as the preventive measures. Fig. 5 Lesion-Specific Details represents the functionality of the system in terms of the condition information provided to the user, where the system offers various forms of information such as the symptoms, causes, as well as the preventive measures.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

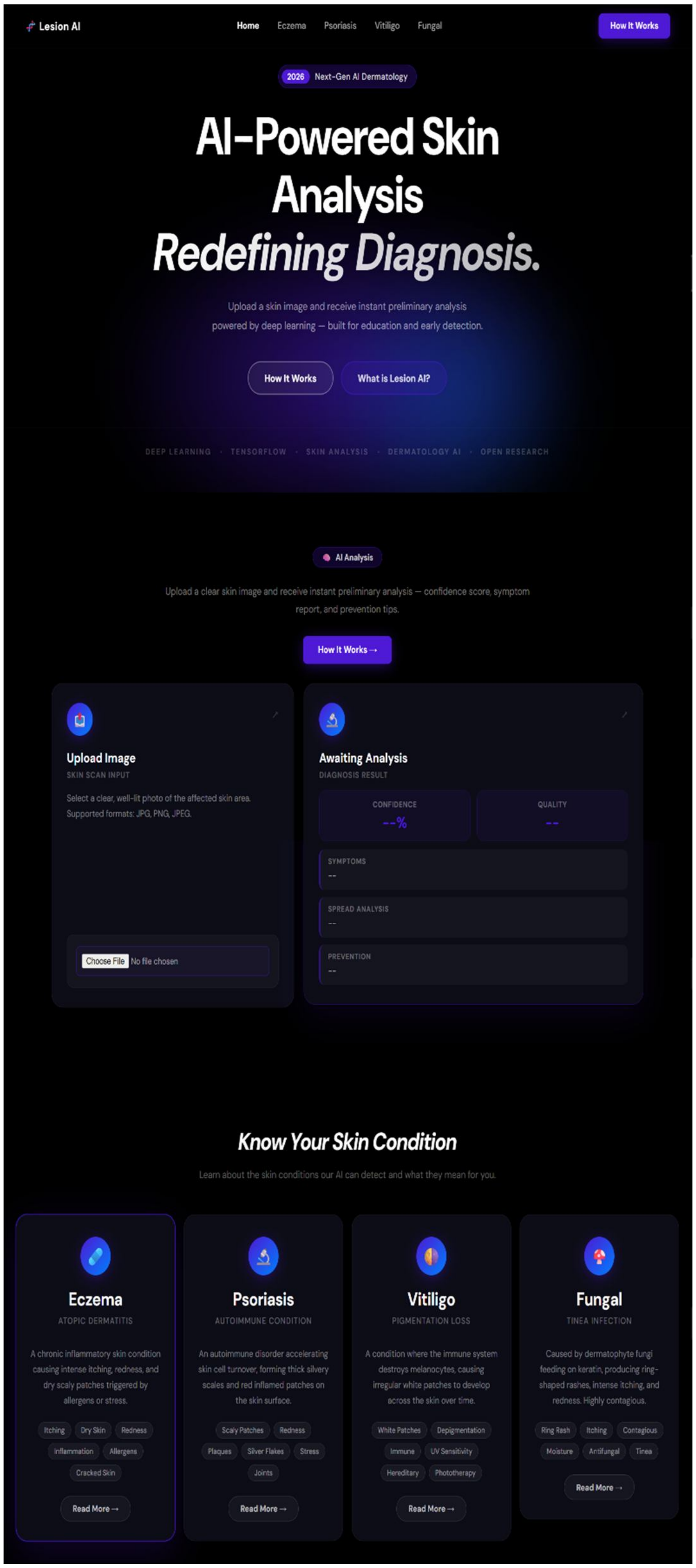

Fig. 2 Home Page Interface

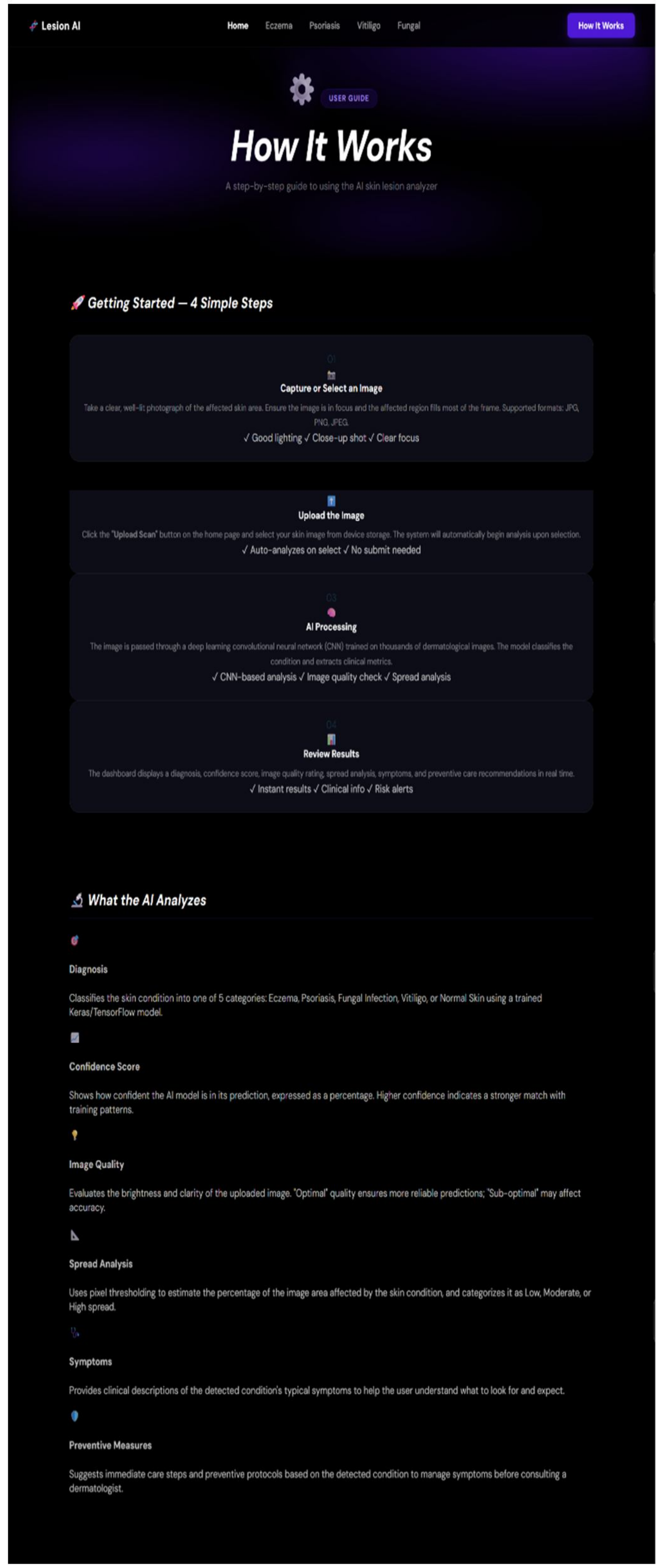

Fig. 3 Internal System Working

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

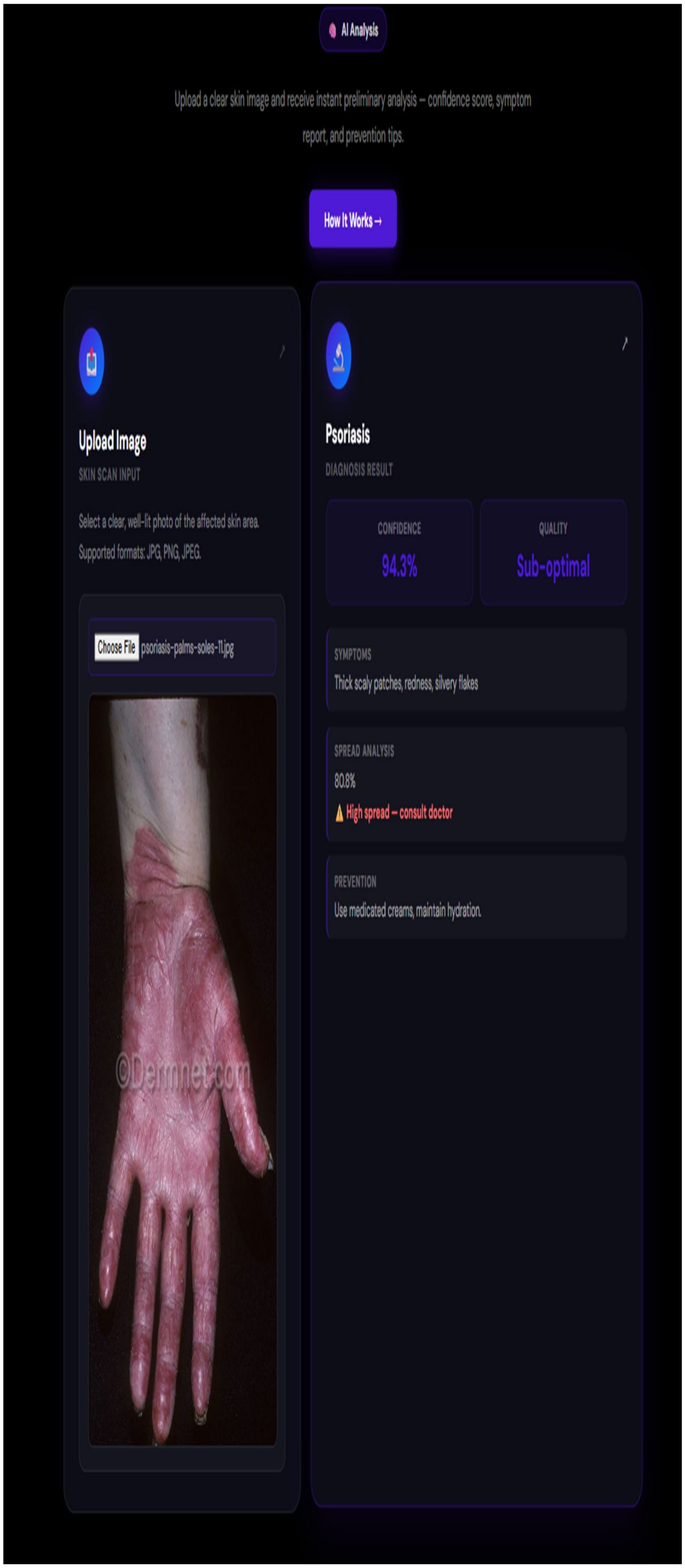

Fig. 4 System Analysing the Lesion

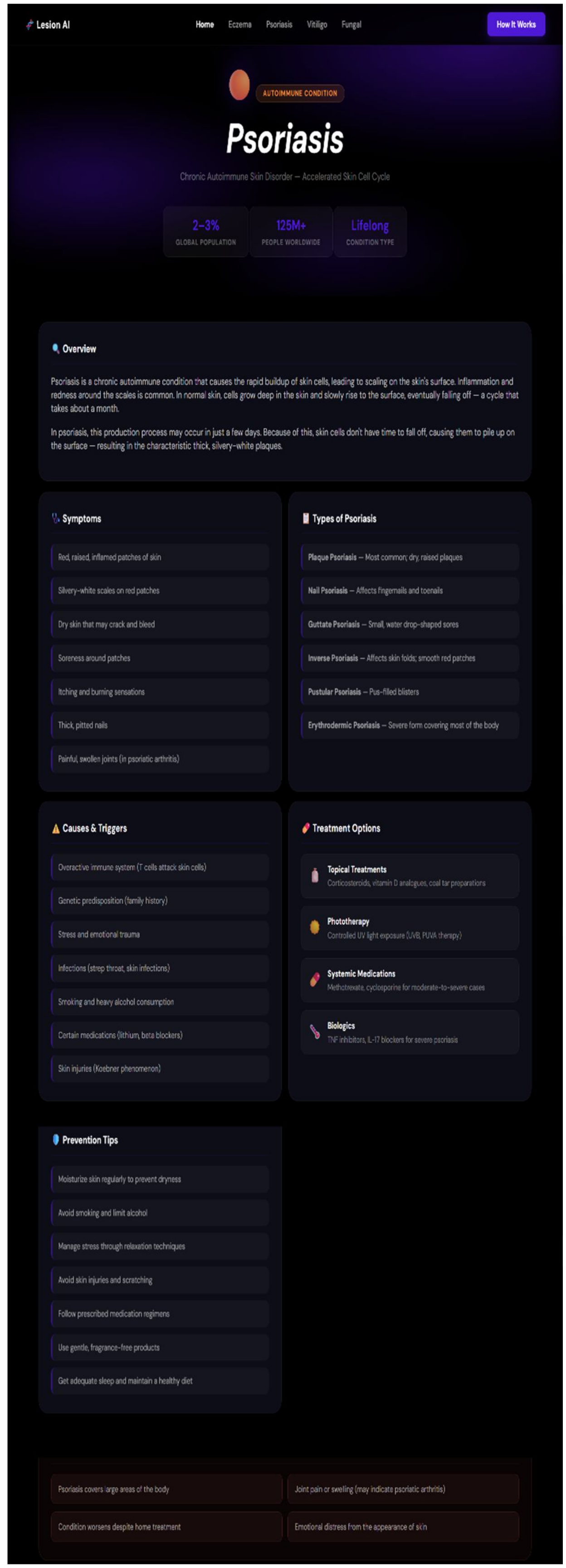

Fig. 5 Lesion-Specific Details

V. CONCLUSIONS

The framework that is proposed will be helpful in providing a practical and efficient solution to automate the interpretation of the lesion. Instead of providing simple classification output from the system, the framework will be helpful in im-proving the functionality of the system, as it will involve the assessment of the quality of the image, spread-based analysis, and addition of information to the system. This will be helpful in improving the output of the system, as it will be more user-friendly. The results obtained from the system indicate that it is performing well even when the input is changed appropriately. This is because the system is properly preprocessed and analyzed, and the addition of confidence calibration will be helpful in improving the output, as it will provide a better understanding of the output. Similarly, the addition of spread-based analysis will be helpful in providing a better understanding. This framework can be effectively applied in preliminary analysis scenarios where simple and easily accessible results are necessary. Possible improvements may be made to the boundary detection mechanism by using advanced segmentation techniques, improving robustness to different imaging conditions, and extending the system to handle more categories. This framework has the potential to evolve into a more comprehensive assistive tool for intelligent lesion analysis

REFERENCES

[1] A. Esteva, B. Kuprel, R. A. Novoa, J. Ko, S. M. Swetter, H. M. Blau, and S. Thrun, “Dermatologist-level classification of skin cancer with deep neural networks,” Nature, vol. 542, no. 7639, pp. 115–118, 2017.
[2] N. C. F. Codella, V. Rotemberg, P. Tschandl, M. E. Celebi, S. W. Dusza, D. Gutman, and A. Halpern, “Skin lesion analysis toward melanoma detection 2018: A challenge hosted by the ISIC,” Scientific Data, vol. 6, p. 34, 2019.
[3] O. Ronneberger, P. Fischer, and T. Brox, “U-Net: Convolutional networks for biomedical image segmentation,” in Proc. MICCAI, 2015, pp. 234–241.
[4] H. A. Haenssle et al., “Man against machine: Diagnostic performance of a deep learning convolutional neural network,” Annals of Oncology, vol. 31, no. 2, pp. 183–188, 2020.
[5] P. Tschandl, C. Rosendahl, and H. Kittler, “The HAM10000 dataset: A large collection of dermatoscopic images,” Scientific Data, vol. 5, p. 180161, 2018.
[6] T. J. Brinker et al., “Deep learning outperformed dermatologists in melanoma classification,” European Journal of Cancer, vol. 113, pp. 47–54, 2019.
[7] L. Yu, H. Chen, Q. Dou, J. Qin, and P. A. Heng, “Automated melanoma recognition in dermoscopy images via deep learning,” IEEE Trans. Med. Imaging, vol. 36, no. 4, pp. 994–1004, 2017.
[8] R. R. Selvaraju et al., “Grad-CAM: Visual explanations from deep networks,” in Proc. ICCV, 2017, pp. 618–626.
[9] A. Dosovitskiy et al., “An image is worth 16×16 words: Transformers for image recognition,” in Proc. ICLR, 2021.
[10] M. J. Sheller et al., “Federated learning in medical imaging,” Scientific Reports, vol. 10, p. 12598, 2020.
[11] M. Frid-Adar, E. Klang, M. Amitai, J. Goldberger, and H. Greenspan, “GAN-based data augmentation for medical imaging,” IEEE Trans. Med. Imaging, vol. 38, no. 3, pp. 677–685, 2018.
[12] Y. Li and L. Shen, “Skin lesion analysis towards melanoma detection using deep learning,” IEEE Access, vol. 6, pp. 12845–12853, 2018.
[13] G. Litjens et al., “A survey on deep learning in medical image analysis,” Medical Image Analysis, vol. 42, pp. 60–88, 2017.
[14] M. Goyal, T. Knackstedt, S. Yan, and S. Hassanpour, “Artificial intelligence-based image classification methods in dermatology,” J. Amer. Acad. Dermatol., vol. 82, no. 2, pp. 491–499, 2020.
[15] L. Bi, J. Kim, A. E. Feng, and D. Feng, “Automatic skin lesion classification using deep learning,” IEEE J. Biomed. Health Informatics, vol. 21, no. 5, pp. 1343–1353, 2017.
[16] A. Mahbod et al., “Transfer learning for skin lesion classification,” Comput. Methods Programs Biomed., vol. 193, p. 105475, 2020.
[17] A. Krizhevsky, I. Sutskever, and G. Hinton, “ImageNet classification with deep convolutional neural networks,” in Proc. NeurIPS, 2012.
[18] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proc. CVPR, 2016.
[19] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” in Proc. ICLR, 2015.
[20] C. Szegedy et al., “Going deeper with convolutions,” in Proc. CVPR, 2015.
[21] M. Tan and Q. Le, “EfficientNet: Rethinking model scaling for convolutional neural networks,” in Proc. ICML, 2019.
[22] I. Goodfellow et al., “Generative adversarial networks,” in Proc. NeurIPS, 2014.
[23] L. Perez and J. Wang, “The effectiveness of data augmentation in image classification using deep learning,” arXiv preprint arXiv:1712.04621, 2017.
[24] Q. Abbas, M. E. Celebi, and I. F. García, “Skin tumor classification using machine learning,” Pattern Recognition, vol. 47, no. 2, pp. 628–637, 2013.
[25] J. Zhang, Y. Xie, Q. Wu, and Y. Xia, “Medical image classification using deep learning: A survey,” Neurocomputing, vol. 339, pp. 197–206, 2019.
[26] M. Combalia et al., “BCN20000: Dermoscopic lesions in the wild,” arXiv preprint arXiv:1908.02288, 2019.
[27] G. Argenziano et al., “Dermoscopy: A tutorial,” J. Amer. Acad. Dermatol., vol. 48, no. 5, pp. 679–693, 2003.
[28] H. K. Jeong, C. Park, R. Henao, and M. Kheterpal, “Deep learning in dermatology,” Dermatology Reports, 2022.
[29] J. Kawahara and G. Hamarneh, “Deep features for skin lesion classification,” in Proc. IEEE EMBC, 2016.
[30] N. C. F. Codella et al., “Deep learning ensembles for melanoma recognition,” in Proc. ISBI, 2016.