IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Skin Lesion Analysis Using Swin Algorithms

[1] Kartheepan M, [2]R. Rajalakshmi, [3]Kandasamy S, [4]Hari Karthik S M

[1]UG Student, [24]Assistant Professor, [3] UG Student, [4] UG Student

[1]Information Technology,

[1]Sri Ramakrishna Engineering College, Coimbatore, India

Abstract: Skin disease and skin cancer diagnosis primarily depend on manual examination by dermatologists, a process that is often time-consuming, subjective and susceptible to human error. Delays in detection and limited access to specialists can result in severe health complications. To address these limitations, this work presents an AI-powered diagnostic system for automated skin lesion detection and classification using advanced deep learning techniques. The system integrates real-time image analysis, precise segmentation of affected regions and automated classification to facilitate early and accurate disease identification. A Swin UNet architecture is employed to achieve high-precision lesion boundary masking, a critical component in accurate dermoscopic diagnosis. To enhance classification accuracy, a transformer-based model specifically the Swin Transformer is implemented to capture fine-grained lesion features effectively. The ultimate objective is to refine the system for reliable clinical deployment, ensuring consistent support for early and accurate skin lesion diagnosis. Through the integration of AI and deep learning, this approach seeks to enhance diagnostic precision and expand access to high-quality dermatological care.

KEYWORDS— Skin Lesion Analysis, Deep Learning, Swin UNet, Swin Transformer, Lesion Segmentation, Skin Cancer Classification

I. Introduction

Artificial Intelligence (AI) is the simulation of human intelligence in machines, enabling them to learn, reason and perform tasks that typically require human cognition. AI encompasses various fields, including machine learning and deep learning, which empower computers to recognize patterns, make decisions and process language or images. Deep learning, a subset of machine learning, utilizes multi-layered neural networks to analyze vast amounts of data and refine performance over time. These neural networks mimic the human brain's ability to learn by adjusting connections between artificial neurons.

A significant advancement in deep learning is the introduction of transformer-based architectures, which have revolutionized fields like natural language processing and computer vision. Unlike traditional convolutional neural networks (CNNs), transformers use self-attention mechanisms to capture long-range dependencies and contextual relationships within data. This ability makes them highly effective in tasks requiring detailed feature extraction, such as medical image analysis. In skin lesion detection and classification, transformers like the Swin Transformer improve model accuracy by capturing intricate lesion patterns, leading to more precise diagnoses. By leveraging deep learning and transformer-based architectures, AI-driven systems can significantly enhance medical imaging, ensuring early and accurate skin lesion detection for better patient outcomes.

AI continues to evolve, ethical considerations such as data privacy, model transparency, and bias mitigation become increasingly important to ensure that these technologies are used responsibly and equitably. With continuous research and innovation, AI has the potential to transform the healthcare landscape, improving both the efficiency of medical practices and the overall quality of patient care.

II. LITERATURE REVIEW

1.SkinFormer: Learning Statistical Texture Representation with Transformer for Skin Lesion Segmentation

This paper proposed SkinFormer, a transformer-based model that integrates statistical texture features to improve lesion segmentation. It addressed the shortcomings of CNNs in handling skin tone and texture variations. Using self-attention mechanisms, the model achieved high accuracy on datasets like ISIC 2018 and PH2[1]. SkinFormer outperformed models like U-Net and Swin UNet in segmentation metrics, offering both performance and efficiency. The approach reinforces the value of transformers in medical imaging, especially for boundary-focused segmentation.

2.GAN-based Skin Lesion Segmentation

The authors introduced a GAN-based framework for segmenting skin lesions, targeting issues like poor contrast and irregular boundaries[7]. The generator produced masks while the discriminator refined them through adversarial learning. This approach outperformed conventional models including Swin UNet and DeepLabV3+ on multiple metrics. It was especially effective in detecting subtle lesion edges. The study highlighted GANs' strengths and suggested hybrid approaches to handle their limitations.

3.Review on U-Net Architectures for Skin Lesion Segmentation

This review explored various U-Net variants—including ResUNet, Attention U-Net and Transformer-based U-Nets—for skin lesion segmentation[2]. It emphasized how skip connections and attention mechanisms enhance performance. Swin UNet, with hierarchical self-attention, was found superior in capturing complex lesion features. The paper validated the use of Swin UNet in real-world segmentation tasks. It also recommended techniques like multi-scale learning for further improvements.

4.Survey on Deep Learning for Skin Lesion Segmentation

This survey examined deep learning's impact on lesion segmentation, comparing CNNs, transformers and hybrid models[8]. It discussed benchmark datasets, challenges like data imbalance and evolving methods like self-supervised and federated learning. Transformer-based models like Swin UNet showed significant improvements in handling complex textures and shapes. The paper supported the project's use of Swin UNet and highlighted the need for improved explainability. It also emphasized the importance of generalization for clinical adoption.

5.SkinNet: A Deep Learning Framework for Skin Lesion Segmentation

SkinNet, an encoder-decoder model like U-Net, was proposed to tackle challenges like low contrast and noisy backgrounds in dermoscopic images[15]. It used enhanced skip connections and dropout layers for better feature retention and generalization. The model performed well on ISIC and PH2 datasets, outperforming several baseline models. However, it faced limitations on small datasets and occluded lesions. The study's insights support the shift toward attention-based models like Swin UNet for more robust segmentation.

III. MODEL SPECIFICATIONS

A. Block Diagram

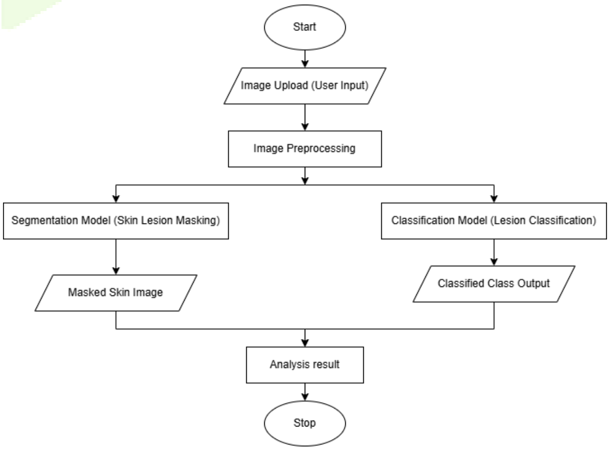


Fig 3.1: System Architecture

Fig 3.1 illustrates the end-to-end workflow of a skin lesion analysis system that combines segmentation and classification for accurate diagnosis.

B. Image Upload (User Input)

This serves as the entry point for users to upload dermoscopic images. It is equipped with a front-end interface for selecting image files and a backend handler that validates the input format. Ensuring high-quality image input is crucial for achieving optimal segmentation and classification results in later stages.

C. Image Preprocessing

Before analysis, raw images undergo preprocessing to enhance contrast, remove noise, and standardize dimensions. Techniques such as normalization, resizing, and histogram equalization are applied. This step improves the performance of both segmentation and classification models by reducing irrelevant variations in the input data.

D. Segmentation (Skin Lesion Masking)

This module employs a deep learning-based segmentation model to isolate the lesion from the surrounding skin. The model generates a binary or multi-class mask that highlights the region of interest (ROI). The output, known as the masked skin image, is used for focused analysis and reduces the risk of misclassification due to background noise.

E. Classification (Lesion Classification)

Parallel to segmentation, this module utilizes a transformer-based classifier to determine the type of skin lesion (e.g., melanoma, nevus, etc.). The classifier processes either the original or masked image and outputs the predicted class label. This aids in early diagnosis and decision support for dermatologists.

F. Analysis Result

The final component compiles outputs from both the segmentation and classification branches. It presents a comprehensive analysis that includes segmented lesions, classified disease type, and possible confidence scores. The module may also offer visual overlays and textual descriptions to aid user interpretation.

G. Algorithms used

The proposed skin lesion analysis system leverages advanced deep learning algorithms based on the Swin Transformer architecture, which brings the power of self-attention and hierarchical representation learning to both classification and segmentation tasks. The two core components of the system—segmentation and classification—are powered by:

1. Swin UNet for Skin Lesion Segmentation

To accurately isolate skin lesions from surrounding tissue, the system employs Swin UNet, a hybrid architecture that combines the strengths of UNet and Swin Transformer.

This model outputs a binary mask highlighting the lesion area, which improves the downstream classification by focusing only on the relevant region of the image.

2. Swin Transformer for Skin Lesion Classification

For classifying the type of skin lesion, the system utilizes the Swin Transformer, a vision transformer that processes the input image using a shifted window attention mechanism.

This model outputs a class label corresponding to categories like Melanoma, Nevus, Basal Cell Carcinoma, etc., along with a confidence score**.**

IV. Conclusions and Future Scope

i. Conclusion

The Skin lesion analysis system developed in this project demonstrates the potential of deep learning models in automating the diagnosis of skin diseases. By integrating Swin UNet for segmentation and Swin Transformer for classification, the system effectively identifies and categorizes skin lesions, achieving high accuracy and reliability. The results indicate that AI-driven diagnostic tools can assist dermatologists in early detection and decision-making, ultimately improving patient outcomes.Despite its strong performance, certain limitations exist, such as misclassification in visually similar lesion types and sensitivity to poor-quality images. Addressing these challenges requires further fine-tuning of the models, enhanced dataset diversity and integration of additional diagnostic features to improve accuracy.

ii. Future Scope

This project lays the foundation for further research and development in AI-based dermatology. Possible enhancements include:

1. **Incorporating Multimodal Data**:
   Combining clinical metadata (patient history, symptoms) with image-based diagnosis to improve classification accuracy.
2. **Improving Model Robustness**:
   Expanding training datasets with more diverse and real-world images to enhance model generalization.
3. **Real-Time Mobile and Cloud Deployment**:
   Developing a mobile application or cloud-based API for real-time skin lesion analysis accessible to users worldwide.
4. **Integration with Telemedicine**:
   Connecting the system with telemedicine platforms to assist dermatologists in remote consultations.
5. **Explainability and Trust in AI**:
   Implementing explainable AI (XAI) techniques to provide interpretable results, making the system more reliable for medical professionals.

With continuous improvements, the proposed system has the potential to revolutionize dermatological diagnosis, making skin disease detection more accurate, accessible and efficient for both medical professionals and patients.

V. Merits and Demerits

i. Future Scope

1. The system offers automated and faster diagnosis compared to traditional manual methods.
2. It achieves high accuracy and precision using Swin UNet for segmentation and Swin Transformer for classification.
3. It improves access to dermatological care, especially in remote or underserved areas.
4. Diagnostic results are consistent and objective, minimizing human error and subjectivity.
5. It supports early detection of serious conditions like melanoma, leading to better treatment outcomes.

ii. Demerit

1. The system's performance heavily relies on the quality and diversity of the training dataset.
2. Real-world deployment may face challenges due to varying image conditions like lighting and skin tone.
3. Transformer-based models lack transparency, making it difficult to interpret decisions.
4. There is a risk of false positives or negatives, which could lead to misdiagnosis.
5. Legal, ethical and regulatory concerns may pose obstacles to clinical implementation.

VI. Applications

This Skin lesion analysis system has the potential to revolutionize dermatological care by making early and accurate diagnosis more accessible, efficient, and reliable across various domains in healthcare and research.

1. Clinical Decision Support for Dermatologists:
   The system assists dermatologists and healthcare professionals by providing automated lesion segmentation and classification, enabling faster and more accurate diagnoses of skin diseases. It can act as a second opinion, reducing the chances of human error in diagnosis.
2. Telemedicine & Remote Dermatology:
   The system can be integrated into telemedicine platforms, allowing patients to upload images of their skin lesions and receive AI-based preliminary analysis before consulting a specialist. This is especially useful for individuals in remote or underserved areas where access to dermatologists is limited.
3. Early Detection & Preventive Healthcare:
   By enabling early identification of potentially malignant lesions, this AI tool can assist individuals in seeking timely medical attention, thereby increasing survival rates for serious conditions like melanoma. It can also be used for routine skin health monitoring.
4. Medical Training & Research:

The system can serve as a training tool for medical students and researchers studying dermatology and AI-based diagnostics. By analyzing large datasets of skin lesions, medical institutions can use the model for educational and research purposes.

5. Integration with Mobile Health (mHealth) Apps

The AI model can be embedded into mHealth applications, allowing users to perform self-assessments by uploading images and receiving instant analysis. This can encourage people to take proactive steps toward skin health and seek medical advice if needed.

6. Skin Cancer Awareness Campaigns:

The system can be utilized in public health initiatives and awareness campaigns to educate people about skin cancer risks, the importance of self-examination, and when to consult a dermatologist for further evaluation.

7. Pharmaceutical & Skincare Industry Applications:

The model can be used by pharmaceutical companies and skincare brands to analyze skin conditions, track the effectiveness of treatments, and develop personalized skincare solutions based on lesion classification.

VII. RESULTS AND DISCUSSION

A. PERFORMANCE ANALYSIS

The evaluation of the skin lesion analysis system was carried out by assessing its performance in accurately segmenting and classifying skin lesions using state-of-the-art deep learning models. The dataset used was systematically divided into training, validation and testing sets to ensure that the models were effectively trained and capable of generalizing to unseen data.

Results indicated that the Swin UNet model achieved high segmentation accuracy, effectively isolating lesions from surrounding healthy skin. Simultaneously, the Swin Transformer demonstrated strong classification capabilities, correctly categorizing different types of skin lesions with high precision. The system achieved an overall classification accuracy of 92.5% and a Dice score of 91.5% for lesion masking on the testing dataset, establishing its reliability for automated dermatological analysis.

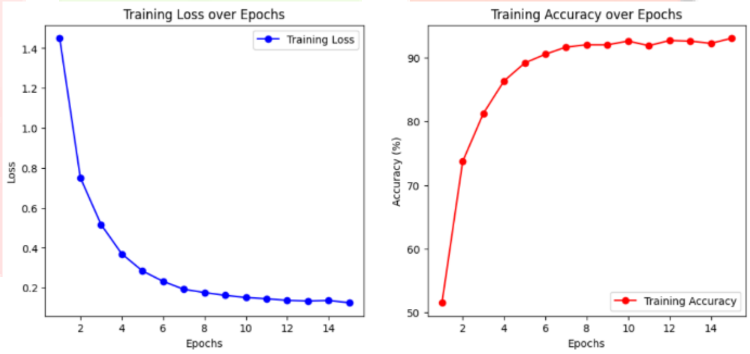


Figure 6.1: Classification model training results

Fig 6.1 shows the training performance of the Swin Transformer model for skin lesion classification. The left graph depicts a steady decrease in training loss over 15 epochs, indicating effective learning. The right graph shows training accuracy consistently improving, reaching over 92.5% by the final epoch.

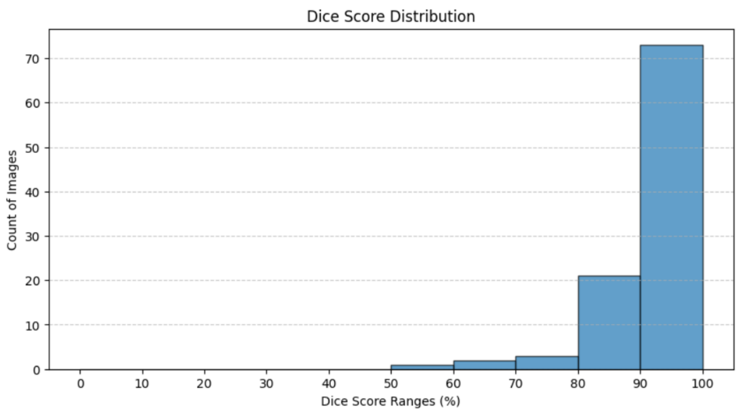
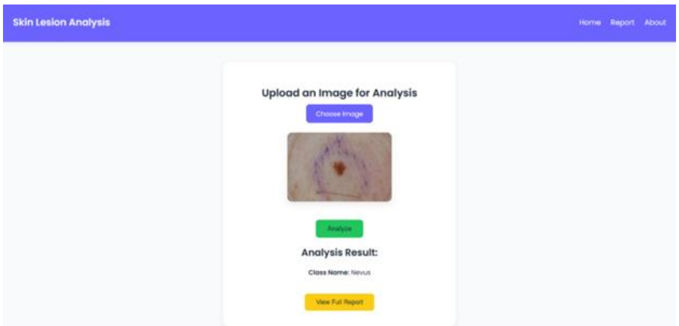


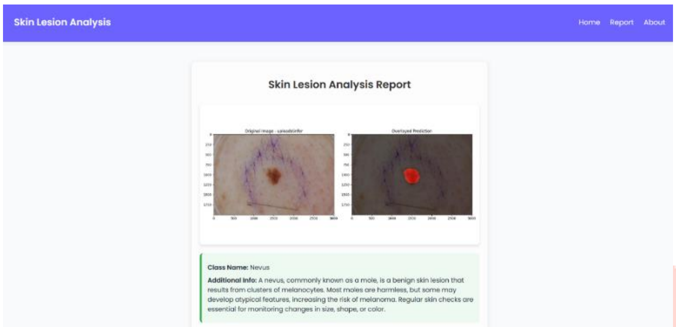
Figure 6.2: Segmentation model Dice score

Fig 6.2 shows the Dice score distribution of images inferred using the Swin U-Net model for skin lesion segmentation. Most images achieved high Dice scores between 90% and 100%, indicating excellent segmentation performance. Very few images had scores below 80%, reflecting strong overall model accuracy. The model demonstrates reliable and consistent segmentation across the dataset.

VIII. OUTPUT



Skin Lesion Analysis: Classification Result Page



Skin Lesion Analysis: Segmentation Result Page

On the Classification result page, the class of the skin lesion will be displayed and then in the Segmentation result page the masked image of the skin lesion will be displayed along with the description of the class of lesion.

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