Skin Cancer Detection Using Deep Learning

Logesh P[1], Ms Abinaya S[2], Dr. Malathi[3]
[1]*Student, Information Technology. SKACAS Coimbatore*
[2]*B. Sc., MCA, Information Technology. SKACAS Coimbatore*
[3]*MCA., MPhil., M.Sc. (Yoga)., MSc (Maths)., NET, PhD, Faculty, Information Technology SKACAS Coimbatore*

Abstract— **Skin cancer is one of the most common and potentially life-threatening diseases, where early detection plays a crucial role in effective treatment. This project presents an AI-powered system for automatic skin cancer detection using deep learning techniques. The model is built using EfficientNet-B0 architecture in PyTorch to classify dermoscopic images into nine different skin disease categories, including both benign and malignant conditions. A user-friendly Gradio interface allows users to upload skin images and receive instant predictions along with confidence scores and highlighted regions using Grad-CAM visualization. The system also provides medical guidance by suggesting consultation with dermatologists or cancer hospitals based on the prediction. By enabling fast and accurate preliminary screening, the system supports early diagnosis and improves accessibility to healthcare assistance.**

Index Terms— Skin cancer detection, Deep learning, EfficientNet-B0, Image classification, PyTorch, GradCAM, Dermoscopic images, medical image analysis, Gradio interface, Early diagnosis

I. INTRODUCTION

Skin cancer is a common and potentially life-threatening disease where early detection is essential for effective treatment. Traditional diagnostic methods such as visual inspection and biopsy are time-consuming, subjective, and depend on expert availability. This creates a need for an automated and accurate system for early skin cancer detection.
To address this, a deep learning-based system using EfficientNet-B0 is developed to classify dermoscopic images into nine skin disease categories, including benign and malignant conditions.
Image preprocessing and Grad-CAM visualization are used to improve accuracy and interpretability. A user-friendly Gradio interface allows users to upload images and receive instant predictions with confidence scores and medical guidance. This system supports early screening and improves accessibility to healthcare assistance.

II. PROBLEM STATEMENT

Skin cancer is one of the most common and serious diseases, where early detection is crucial for effective treatment and may not be easily accessible in remote or underserved areas, leading to delayed diagnosis and increased health risks.
Manual examination can also result in misdiagnosis, especially in early stages where symptoms are less visible. The lack of an efficient, automated system makes large-scale screening difficult and limits timely medical intervention. Hence, there is a critical need for an accurate, automated, and real-time skin cancer detection system that can assist in early diagnosis and provide accessible healthcare support.

III. DOMAIN

The study lies within Healthcare Analytics, focusing on skin cancer detection using deep learning and medical image classification. Skin diseases, particularly cancerous lesions, pose significant health risks and require early diagnosis for effective treatment.
By integrating artificial intelligence and computer vision techniques, the system enables accurate and timely detection of skin conditions from dermoscopic images. This approach supports early diagnosis, improves clinical decision-making, and enhances accessibility to healthcare services, contributing to better patient outcomes.

IV. LITERATURE REVIEW

Recent research in the field of medical image analysis has focused on improving skin cancer detection using deep learning techniques.

Ian Goodfellow et al. (2016) [1] introduced foundational deep learning concepts that have enabled the development of advanced image classification models. Alex Krizhevsky et al. (2012) [2] demonstrated the effectiveness of Convolutional Neural Networks (CNNs) for image classification tasks, significantly improving accuracy in visual recognition problems.

Further advancements were made by Kaiming He et al. (2016) [3], who proposed the ResNet architecture, enabling deeper networks and improved performance in medical image analysis. Similarly, Mingxing Tan and Quoc Le (2019) [4] introduced Efficient Net, which achieved better accuracy with fewer parameters, making it suitable for real-time applications. Studies using dermoscopic image datasets have shown that deep learning models can achieve high accuracy in detecting skin cancer, particularly melanoma and other malignant conditions.

In addition, research on explainable AI techniques such as Grad-CAM has improved model interpretability by highlighting important regions in medical images, assisting clinicians in understanding model decisions. However, many existing systems focus only on classification accuracy and lack user-friendly deployment, real-time accessibility, and practical medical assistance features.

In conclusion, unlike previous works that primarily focus on model performance, the proposed system provides a complete end to-end solution using EfficientNet-B0 and a Gradio-based interface. It offers real-time skin disease detection, confidence scoring, visualization of affected regions, and intelligent medical guidance by redirecting patients to nearby dermatologists or cancer hospitals based on their location. This makes the system more practical, accessible, and valuable for early diagnosis and healthcare support.

V. DATA PREPROCESSING

The pre-processing stage prepares dermoscopic skin images for deep learning by resizing them to 224×224 pixels suitable for the EfficientNet-B0 model and normalizing pixel values to ensure stable training and faster convergence. Data augmentation techniques such as flipping, rotation, and zooming are applied to increase dataset diversity, improve generalization, and reduce overfitting. The dataset consists of nine classes: Actinic Keratosis, Basal Cell Carcinoma, Dermatofibroma, Melanoma, Nevus, Pigmented Benign Keratosis, Seborrheic Keratosis, Squamous Cell Carcinoma, and Vascular Lesion, and is split into 80% training and 20% testing sets to evaluate model performance on unseen data. These pre-processing steps enhance learning efficiency, improve accuracy, and ensure reliable classification of different skin diseases.

VI. METHODOLOGY

A dataset of labelled dermoscopic skin images was pre-processed using resizing, normalization, and data augmentation techniques to improve model robustness and generalization. A deep learning model based on EfficientNet-B0 was trained to classify nine skin diseases, including Actinic Keratosis, Basal Cell Carcinoma, Dermatofibroma, Melanoma, Nevus, Pigmented Benign Keratosis, Seborrheic Keratosis, Squamous Cell Carcinoma, and Vascular Lesion. The trained model was integrated with a Gradio-based user interface, allowing users to upload skin images and instantly receive predictions along with confidence scores, highlighted regions using

Grad-CAM, and appropriate medical guidance. The system also redirects users to nearby dermatologists or cancer hospitals based on their location, enabling timely diagnosis and healthcare support.

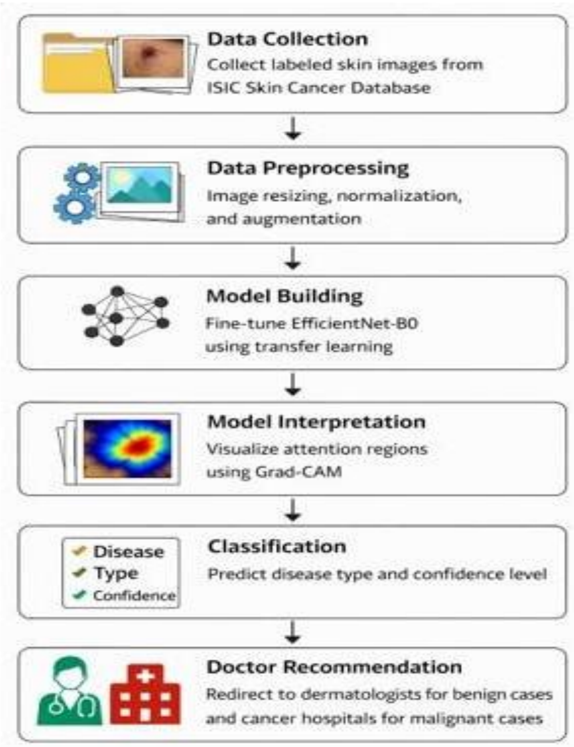

Fig.1 Process Flow

Figure 1 represents the system process flow, where dermoscopic skin images are preprocessed, the EfficientNet-B0 model predicts the skin disease type, and the results including classification, confidence score, highlighted regions (Grad-CAM), and medical guidance are displayed through the skin disease class along with confidence scores and highlighted regions using Grad-Gradio interface.

VII. RESULT AND INTERPRETATION

The trained deep learning model based on EfficientNet-B0 was deployed using a Gradio interface to provide an accessible AI-powered tool for users. The system allows easy image upload, processes dermoscopic images in real time, and outputs the predicted CAM visualization. Additionally, the system provides meaningful medical guidance by identifying whether the condition is benign or malignant and redirecting users to dermatologists or nearby cancer hospitals based on their location. By combining deep learning with a user-friendly interface, the solution supports early detection, improves diagnostic efficiency, and enhances accessibility to healthcare services.

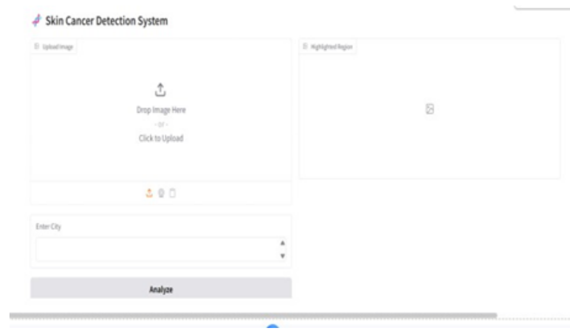

Fig 2 Input Image

accuracy and is deployed through a Gradio interface, enabling users to upload skin images and receive real-time predictions. The system provides disease classification, confidence scores, and highlighted regions using Grad-CAM, along with medical guidance by redirecting users to dermatologists or cancer hospitals based on the predicted condition and location. This approach supports early detection, improves diagnostic efficiency, and enhances accessibility to timely healthcare assistance.

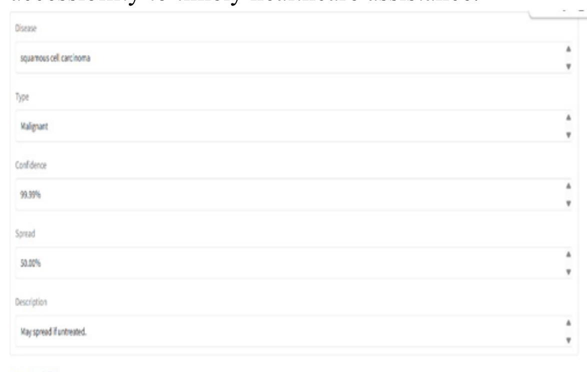

Fig 3 prediction GUI interface

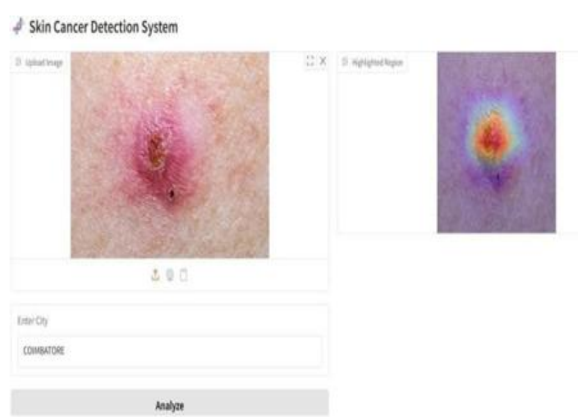

Fig 4 Predicted output interface

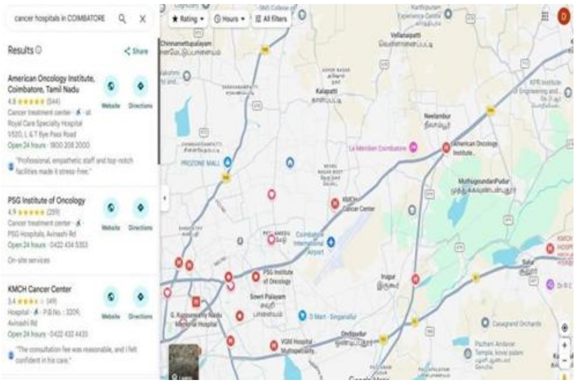

Fig 5 Redirecting to nearest hospital

VIII. CONCLUSION

This paper presents a deep learning–based system for skin cancer detection using the EfficientNet-B0 model to classify dermoscopic images into nine categories: Actinic Keratosis, Basal Cell Carcinoma, Dermatofibroma, Melanoma, Nevus, Pigmented Benign Keratosis, Seborrheic Keratosis, Squamous Cell Carcinoma, and Vascular Lesion. The model achieves high

IX. FUTURE WORK

The system can be further enhanced by adopting advanced deep learning architectures such as Efficient Net variants, Vision Transformers (ViT), and hybrid models to improve classification accuracy. Integration of additional clinical metadata (such as patient history, age, or lesion characteristics) can support better diagnosis and severity prediction. The use of Explainable AI techniques like Grad-CAM, LIME, and SHAP can improve transparency and trust in model predictions. Expanding the dataset with more diverse dermoscopic images will strengthen model generalization. Additionally, deploying the model as a mobile application using TensorFlow Lite, enabling real-time camera-based detection, and integrating location-based services to guide users to nearby dermatologists or cancer hospitals can make the system more practical and accessible. Multi-task learning can also be incorporated to estimate disease severity and affected area, making it a more comprehensive clinical decision support system.

REFERENCES

[1] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2016.

[2] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2016, pp. 770–778.

[3] M. Tan and Q. Le, "EfficientNet: Rethinking model scaling for convolutional neural networks," in *Proc. Int. Conf. Mach. Learn. (ICML)*, 2019, pp. 6105–6114.

[4] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," in *Advances in Neural Information Processing Systems (NeurIPS)*, 2012, pp. 1097–1105.

[5] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," in *Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent. (MICCAI)*, 2015, pp. 234–241.

[6] R. R. Selvaraju *et al.*, "Grad-CAM: Visual explanations from deep networks via gradient-based localization," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, 2017, pp. 618–626.