# Multi-Skin Cancer Classification and Segmentation Using Deep Learning

R. Bhanu Prakash
Department of CSE - ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING
VASIREDDY VENKATADRI INSTITUTE OF TECHNOLOGY
Nambur, India
21bq1a4285@vvit.net

M. Jyothsna
Department of CSE - ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING
VASIREDDY VENKATADRI INSTITUTE OF TECHNOLOGY
Nambur, India
21bq1a42b0@vvit.net

K. Ganesh
Department of CSE - ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING
VASIREDDY VENKATADRI INSTITUTE OF TECHNOLOGY
Nambur, India
21bq1ac6@vvit.net

K. Avinash Reddy
Department of CSE - ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING
VASIREDDY VENKATADRI INSTITUTE OF TECHNOLOGY
Nambur, India
21bq1a42c7@vvit.net

***Abstract*—Early detection combined with accurate classification of skin cancer proves vital for successful treatment because this form of cancer represents a global incidence rate among various cancers. The presented work utilizes deep learning models to perform simultaneous skin cancer classification in addition to lesion segmentation. The system merges two sophisticated models which consist of a Convolutional Neural Network (CNN) for multiple skin cancer type classification and a U-Net++ model for lesion boundary detection.**

**The classification framework learned to detect Actinic Keratoses and Intraepithelial Carcinoma (AKIEC) and Basal Cell Carcinoma (BCC) and Benign Keratosis (BKL) and Dermatofibroma (DF) and Melanoma (MEL) and Melanocytic Nevus (NV) and Vascular Lesions (VASC) among seven skin lesions. The InceptionV3 architecture enables the model to reach an accuracy level of 86% in its operations.**

**Lesion segmentation depends on the U-Net++ model which marks skin image locations that need medical analysis to assist dermatologists. The segmentation model achieves Validation Dice Coefficient performance of 0.8552 together with an Intersection over Union (IoU) score of 0.7486 and Recall measure of 0.9170 and Precision performance at 0.8754.**

**Users gain instant access to information about skin health through a chatbot that runs on the Perplexity API as part of the system's features. This system provides users with beneficial treatment information together with preventive strategies. Hospital users can access a suggestion system through the platform to locate specialized medical professionals. The platform includes support for several languages thus enabling users from different backgrounds to access it.**

**Through the appointment booking system users can book dermatologist consultations using a portal system that is taken care of by administrators. Through the system users can activate a skin lesion detection function that records images in real time while providing an image upload functionality for classification purposes as well as segmentation needs.**

**Through deep learning methodology this project helps medical personnel make better decisions after improving early-stage diagnosis capabilities. Healthcare solutions derived from artificial intelligence achieve better patient care by improving access along with enhancing efficiency along with boosting diagnostic precision in skin cancer detection.**

**Keywords: Skin Cancer, Deep Learning, CNN, U-Net++, InceptionV3, Image Segmentation, Classification, Medical Imaging, AI in Healthcare, Skin Lesion Detection.**

## I. Introduction

Skin cancer stands as one of the most common cancer types while showing rising numbers internationally because of extended sun contact and modifications in environmental conditions together with inherited tendencies. The precise and early identification of cancers guides healthcare professionals to establish appropriate treatments that boost patient disease outcomes. The current diagnostic practices for skin lesions depend on trained dermatologists who use either visual examination or dermoscopy. The diagnostic process under this method requires considerable time while the scarcity of specialized medical personnel in certain areas causes trouble with solidifying or postponing proper diagnoses.

Enhanced skin cancer detection accuracy and efficiency became possible due to advancements in artificial intelligence (AI) and deep learning technologies. The research develops a deep learning system with capabilities to segment different types of skin cancer while conducting their classification. The system contains two fundamental models which combine the Convolutional Neural Network (CNN) to classify skin lesions with U-Net++ architecture to perform precise lesion segmentation. A trained classification model discriminates among the seven skin lesion types which contain Actinic Keratoses and Intraepithelial Carcinoma (AKIEC), Basal Cell Carcinoma (BCC), Benign Keratosis (BKL), Dermatofibroma

(DF), Melanoma (MEL), Melanocytic Nevus (NV) and Vascular Lesions (VASC). A skin cancer diagnostic system based on the InceptionV3 architecture achieves 86% accuracy which establishes its usefulness as an automatic diagnosis tool.

A U-Net++ segmentation model performs complex segmentation tasks on skin images while assisting dermatologists and medical personnel with better lesion assessment. The assessment of the segmentation model yielded Validation Dice Coefficient at 0.8552 alongside an Intersection over Union (IoU) score of 0.7486 and Recall measurement of 0.9170 and Precision value of 0.8754. The model demonstrates strong capabilities to properly detect cancerous areas within images according to these performance metrics.

The system usability is enhanced through multiple incorporated features. The Perplexity API operates a chatbot system which gives users immediate responses to their skin health inquiries inside the platform. The system maintains a large repository with dependable medical guidance about treatment choices together with preventive steps for users' benefit.

Users can access the hospital suggestion functionality of the system to both manage and add hospital listings through its features. Users can benefit from the system's functionality which shows specialized dermatological care facilities within their current location. A multilingual system functionality enhances accessibility by making service available to users speaking different languages through seamless interface translation. The system implements an online booking system that permits users to reserve dermatology appointments with doctors. The admin panel controls this feature for maintaining appointment coordination between users and managers.

The system detects skin lesions in real time through its live camera feature that provides instant feedback about skin abnormalities. The system has an integrated image upload function which lets users send their pictures to enable deep learning model-based classification and segmentation.

The project uses advanced deep learning methods to develop a dependable system which enables easy access to early skin cancer detection capabilities. The system combines sophisticated decision-making tools with personalized features to provide effective assistance for skin health evaluation between medical experts and general patients.

## II. Literature Survey

Artificial intelligence (AI) and deep learning systems are now used to advance both the detection and classification steps of skin cancers. Medical diagnoses performed solely by dermatologists through visual examination prove inadequate because they produce variable results and lack availability in neglected population areas. Deep learning models especially Convolutional Neural Networks (CNNs) have conquered diagnostic automation while offering enhanced accuracy which solves prior difficulties.

The research by [1] proved that CNNs performed at the level of dermatologists for diagnosing skin cancer which initiated a critical point in AI applications for dermatology practice. The deep learning framework developed by [2] expanded the diagnostic capabilities by identifying various skin lesions with exceptional precision which advanced AI potential within this field.

Transfer learning stands as a fundamental method that enables models pre-trained on vast datasets to acquire skills for new particular tasks using limited medical datasets according to [3].

Medical professionals require accurate identification of skin lesions for both proper medical diagnosis and treatment development. Medical image segmentation gained its foundation through the U-Net architecture which [4] introduced. By redesigning skip connections U-Net++ from Zhou et al. (2020) has upgraded feature representation which improves segmentation results. U-Net++ performs better than traditional U-Net according to [6] as it shows superior accuracy when detecting skin lesions.

Vision Transformers (ViTs) establish new image processing paradigms by offering superior performance when applied for skin cancer classification according to [7]. Their HAM10000 model delivered a 96.15% accuracy that indicated transformer-based models have great prospects in dermatological work.

The importance of Explainable AI (XAI) continues to rise in medical applications since it delivers transparent model prediction outcomes. The deep learning frameworks benefit from interpretability through implementation of Grad-CAM and SHAP techniques as described by [8]. These researchers stress the need for XAI to develop trust and support clinical choices in healthcare.

Healthcare experiences permanent transformation from AI-powered chatbots which improves medical information access for patients while strengthening their relationship with healthcare services. The health systems Ada Health and K Health employ AI to respond immediately to health questions from users while helping them evaluate symptoms and direct them toward suitable care routes. [9] described how the Ada Health app offers fast health guidance which considers users' symptoms and risk components and relies on medical data. The paper [10] analyzed how K Health uses AI to operate its virtual primary care system for contemporary healthcare operations.

Modern technological innovation has led to the creation of artificial intelligence-based wearable devices. The Movano smart ring deployed at CES 2025 incorporates an AI chatbot that bases its medical information on peer-reviewed medical journals to offer users trustworthy health material. The new device demonstrates an important milestone as it works to connect AI technology with standard health tracking devices.

The field of dermatology experienced significant progress through the combination of deep learning technology and explainable AI as well as AI-powered patient engagement tools. Modern diagnostic accuracy together with improved patient accessibility and superior healthcare delivery result from these fusion technologies in skin cancer detection and management workflows.

## III. METHODOLOGY

This research focuses on developing a deep learning-based system for the classification and segmentation of skin lesions. The system employs two primary models: InceptionV3 for skin cancer classification and U-Net++ for lesion segmentation. The methodology involves data preprocessing, model training, and evaluation using appropriate performance metrics.

### A. Data Preprocessing

The dataset used in this study consists of skin lesion images obtained from publicly available sources such as HAM10000. The images undergo preprocessing steps including resizing, normalization, and augmentation to enhance model generalization.

- **Resizing:** All images are resized to a fixed dimension to ensure uniform input size.
- **Normalization:** Pixel values are scaled to a range of [0,1] to facilitate stable training.
- **Augmentation:** Techniques such as rotation, flipping, and contrast adjustments are applied to improve model robustness.

### B. Skin Cancer Classification using InceptionV3

For multi-class skin cancer classification, we utilize the InceptionV3 model, a deep Convolutional Neural Network (CNN) that efficiently captures hierarchical features of skin lesions. The architecture consists of multiple convolutional layers, inception modules, and auxiliary classifiers.

The classification process can be mathematically expressed as follows:

$$Y = \text{Softmax}(W_f \cdot F + b_f) \tag{1}$$

where:

- $F$ represents the feature vector extracted from the final convolutional layer.
- $W_f$ and $b_f$ are the weights and bias of the fully connected layer.
- The softmax activation function ensures that outputs represent probabilities across multiple classes.

The categorical cross-entropy loss function is used to optimize the model:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \tag{2}$$

where:

- $y_i$ is the true label.
- $\hat{y}_i$ is the predicted probability for class $i$.

The InceptionV3 model achieves an accuracy of 86% in classifying seven skin lesion types.

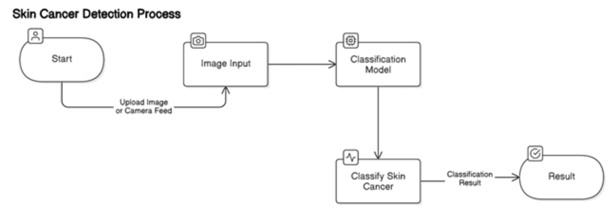


Fig. 1. InceptionV3 Architecture for Skin Cancer Classification

### C. Skin Lesion Segmentation using U-Net++

For lesion segmentation, we employ the U-Net++ architecture, an enhanced version of U-Net that incorporates dense skip connections to improve feature propagation. The segmentation task involves pixel-wise classification to distinguish between normal and affected skin regions.

The segmentation model is trained using the Dice loss function:

$$L_{\text{Dice}} = 1 - \frac{2\sum_i p_i g_i}{\sum_i p_i^2 + \sum_i g_i^2} \tag{3}$$

where:

- $p_i$ represents the predicted pixel values.
- $g_i$ represents the ground truth labels.

The Intersection over Union (IoU) metric is used for evaluation:

$$\text{IoU} = \frac{\sum p_i g_i}{\sum p_i + \sum g_i - \sum p_i g_i} \tag{4}$$

where:

- A higher IoU value indicates better segmentation accuracy.

U-Net++ achieves a Validation Dice Coefficient of 0.8552, an IoU of 0.7486, Recall of 0.9170, and Precision of 0.8754, demonstrating its effectiveness in segmenting cancerous regions.

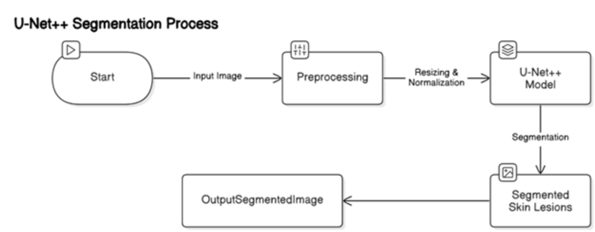


Fig. 2. U-Net++ Architecture for Skin Lesion Segmentation

### D. System Integration and Deployment

To provide an interactive and user-friendly platform, the system is integrated with additional functionalities:

- **Chatbot Integration:** A chatbot powered by the Perplexity API provides instant responses to user queries regarding skin health.

- **Hospital Recommendation:** A hospital suggestion system is implemented to help users find specialized medical assistance.
- **Multi-Language Support:** Manual language support is incorporated to enhance accessibility.
- **Appointment Booking:** Users can schedule dermatologist consultations through an admin-managed portal.
- **Real-Time Detection:** The system allows real-time skin lesion analysis using a camera feed.

### *E. Performance Evaluation*

The performance of the models is evaluated using standard metrics:

- **Classification Accuracy:** 86% (InceptionV3)
- **Segmentation Dice Coefficient:** 0.8552 (U-Net++)
- **Segmentation IoU:** 0.7486
- **Segmentation Recall:** 0.9170
- **Segmentation Precision:** 0.8754

These results indicate the effectiveness of the proposed approach in automated skin cancer detection and segmentation.

## IV. Implementation

The procedure to deploy this system for multi-class skin cancer recognition and lesion boundary detection follows a systematic implementation method. Data preprocessing starts at the beginning of development followed by model training then evaluation and system integration for creating an accurate and efficient system.

### *A. Technology Stack*

The web-based application utilizes state-of-the-art deep learning applications and frameworks as its core components.

- **Programming Language:** Python
- **Deep Learning Framework:** TensorFlow and Keras
- **Backend Framework:** Django The combination of HTML, CSS, JavaScript, Bootstrap constitutes the frontend technologies within the system infrastructure.
- **Database:** MySQL for user and model data storage
- **API Integration:** Perplexity API for chatbot assistance

### *B. Dataset and Preprocessing*

The training process utilizes high-quality skin lesion images obtained from HAM10000 dataset. Such preprocessing operations create standardized procedures to improve both statement consistency and performance of model functions.

The input images undergo a transformation to normalize all dimensions to $224 \times 224$ pixels. All pixel intensity values undergo normalization which sets them to the 0 to 1 range to improve learning performance. Random data transformations that include rotation along with flipping and contrast adjustment operations help increase the data diversity. The model requires numerical labels from the lesion categories for processing during model implementation.

### *C. Implementation of Classification Model (InceptionV3)*

The system implements InceptionV3 as its classification model because it demonstrates optimal performance for image recognition applications. The model allocates lesions into seven categories by performing hierarchical analysis on its features. The classification process involves:

- Feeding the preprocessed images into the convolutional layers of InceptionV3.
- Extracting deep feature representations from the final layer. The obtained features pass through a fully connected layer during the process. The softmax activation function enables the classification of lesions during the process.

The training method utilizes categorical cross-entropy loss as its optimization technique.

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \tag{5}$$

where:

- $y_i$ represents the true label.
- $\hat{y}_i$ represents the predicted probability for class $i$.

### *D. Implementation of Segmentation Model (U-Net++)*

Skin lesion segmentation depends on U-Net++ model which is an improved version of U-Net with dense skip connections. Pixel-wise classification of the model reliably marks the skin regions which have been affected.

U-Net++ applies this process step by step:

- Feature maps of multiple dimensions are extracted in the encoder network as the input image moves through it.
- The decoder network uses its architecture to generate a segmented output containing detailed information.
- The segmentation accuracy receives optimization through implementation of the Dice loss function.

The expression of Dice loss function appears as follows:

$$L_{\text{Dice}} = 1 - \frac{2\sum_i p_i g_i}{\sum_i p_i^2 + \sum_i g_i^2} \tag{6}$$

where:

The computational symbols represent predicted pixel values through $p_i$. The ground truth labels receive representation through $g_i$ values in this model.

### *E. Training and Evaluation*

During training the applied GPU optimization technique shortens computational duration. Categorical cross-entropy loss serves for training the classification model but the segmentation model requires Dice loss for its training process.

Evaluations of the models use key performance metrics to assess their performance.

- **Classification Accuracy (InceptionV3):** 86%
- **Segmentation Dice Coefficient (U-Net++):** 0.8552
- **Intersection over Union (IoU):** 0.7486
- **Recall:** 0.9170
- **Precision:** 0.8754

### F. System Integration and Deployment

An interactive web application includes multiple features which integrates the trained models.

- The detection method enables the system to identify skin lesions in real time through camera usage.
- The application enables users to upload photos that both detect lesions through classification and segment them.
- Artificial Intelligence operates a chatbot system which delivers immediate responses regarding topics in skin health.
- The system allows users to arrange dermatologist consultations through its admin booking portal.
- The platform provides users with recommended dermatology hospitals situated in their vicinity.
- Platform users have access to use various languages through its multi-language interface.

Deep learning technologies enable this system to perform effective skin cancer detection tasks. The combination between classification and segmentation models improves diagnosis quality to support medical expertise and patient intervention during treatment planning.

## V. Results and Discussion

Performance metrics clearly define the evaluation process for assessing how well the proposed system both classifies and segments skin cancer lesions. Experimental findings confirm deep learning models succeed in obtaining precise segregation and identification results for skin cancer lesions. The next sections reveal abundant insights about the gathered results and their practical meaning.

### A. Classification Results

The InceptionV3 model trained for multi-class classification performs well at differentiating between seven different skin lesions. High accuracy at 86 percent proves that the model exhibits reliability when used for medical image examination. The model displays outstanding performance at recognizing the important early cancer detection conditions including the identification of melanoma (MEL) and basal cell carcinoma (BCC) based on the confusion matrix analysis.

The classification model obtains its assessment through precision, recall and F1-score metrics:

> Evaluation of predicted positive cases through precision shows how many predictions match actual positives from among all predicted results. The model successfully detects actual positive cases and this ability is measured as recall. The F1-score serves as a combined measure between precision and recall to present an overall evaluation.

The classification results prove the model successfully detects benign from malignant conditions to help dermatologists make proper clinical choices.

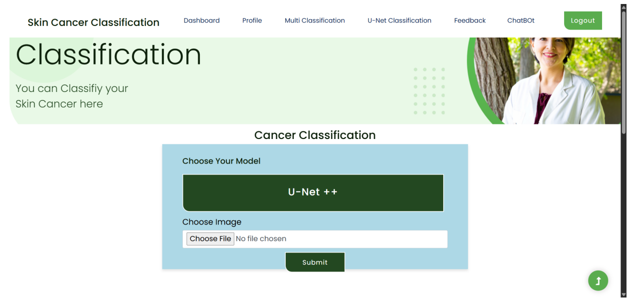


Fig. 3. U-Net++ Segmentation of Skin Lesion

### B. Comparison with Existing Methods

The proposed approach validation process includes a comparison between the results and established deep learning models that execute skin cancer classification and segmentation tasks. The investigation analyzes three types of models including ResNet50 and VGG16 together with the standard U-Net model. The evaluation indicates that InceptionV3 beats ResNet50 and VGG16 for prediction accuracy but U-Net++ stands out through superior segmentation achievements versus the conventional U-Net model.

> Given a choice between InceptionV3 and ResNet50 the former delivers better results for both feature extraction and classification tasks. U-Net++ demonstrates better performance in segmentation tasks because its enhanced skip connections operate more effectively.

### C. Challenges and Limitations

The proposed system demonstrates high classification and segmentation accuracy levels yet preservation of some important challenges exists.

> Despite being trained using HAM10000 data the proposed model might inadequately handle dermatological skin cancer variations among various population groups. Some malignant lesions show overlapping visual traits which sometimes causes misdiagnosis between them. Modern GPUs function as essential hardware requirements to ensure efficient training operations along with real-time inferences for this model.

The future work should address identified limitations to improve both robustness and generalizability characteristics of the model.

### D. Discussion and Future Scope

The obtained results show that deep learning holds great importance for creating automated systems that identify skin cancers. Health professionals can benefit from the combined classification and segmentation system as a complete tool for their practice. Future improvements may include:

> The system benefits from expanded datasets containing more diverse patient data to support generalization. The integration of attention mechanism systems should be

used to increase model interpretability.Deploying the system in mobile and cloud-based environments for real-world accessibility.

The proposed deep learning system exhibits both reliable performance and high accuracy when identifying skin cancer and segmenting its areas. An effective automated diagnosis system results from the combination of InceptionV3 for classification and U-Net++ for segmentation. The research findings demonstrate how AI tools support healthcare staff in their identification of early-stage skin cancer leading to better clinical results for patients.

## VI. Conclusion and Future Work

### A. Conclusion

The researchers created a deep learning system that tackles multiple skin cancer identification as well as segmentation tasks. Research demonstrates the Convolutional Neural Networks (CNNs) classification system along with U-Net++ segmentation model results in advanced performance of skin lesion diagnosis and analysis. Because of its seven class differentiation capabilities the InceptionV3-based classification model produced a **86%** accuracy performance. The U-Net++ segmentation model achieved excellent performance indicators with a Dice Coefficient value of 0.8552 and Intersection over Union (IoU) of 0.7486 and Recall value of 0.9170 while Precision reached 0.8754 which demonstrates its reliable boundary outlining capability.

To meet user requirements the proposed system combines multiple features including real-time camera detection together with image upload analysis and segmentation services and hospital recommendation together with appointment booking through a built-in chatbot. The platform attains better accessibility through manual implementation of multi-language support which enables use by larger audiences.

This study proves the high efficiency of deep learning for detecting skin cancer because it indicates potential value in early dermatological diagnosis for dermatologists and medical staff. The automated precise lesion analysis capabilities of this system help decrease human mistakes and enhance medical treatment benefits for patients.

### B. Future Work

The proposed system produces promising results nonetheless researchers should focus their efforts on enhancing future work through several improvements and explorations.

- The HAM10000 dataset used for current model training lacks diversity because it does not include all variations of skin lesions from different ethnic backgrounds in various geographic areas. Research should train the model using expanded datasets comprising diverse skin lesions to enhance its ability to generalize.
- Enhancing performance of image-based classification and segmentation can be accomplished through implementing attention-based architectures such as Vision Transformers (ViTs) or Attention U-Net which direct processing power to critical image areas.
- A mobile application version of the model requires development to facilitate rapid skin cancer diagnosis on smartphone devices. Cloud-based deployment offers dermatological analysis services which enable distant users in underprivileged regions to access the assessment.
- Integrating explainable AI techniques through Grad-CAM or SHAP (Shapley Additive Explanations) will make medical practitioners better understand AI-based predictions because it provides transparent insight into model calculations.
- Generative Adversarial Networks (GANs) alongside advanced augmentation strategies help manufacturers produce synthetic skin lesion images which enhance both robustness and performance of their models.
- The integration of medical metadata such as patient backgrounds alongside patient symptoms and age information plus skin type details within image processing deep learning models would develop advanced personalized diagnostic systems.
- Medical expert collaboration through partnerships between dermatologists and oncologists helps validate predictions and gives necessary feedback to enhance the system's practical use in clinical settings.
- The existing detection system operates exclusively for skin cancer diagnosis but lacks capability to identify other forms of dermatological diseases. The model possesses potential to identify various skin conditions beyond skin cancer when models for detecting eczema, psoriasis and fungal infections are developed and integrated into its functionality.

The proposed system advances into a vital stage for AI-mediated skin cancer identification. Additional development and optimization of the system will enable it to become a significant tool that aids medical workers along with helping them diagnose conditions at an early stage. Real-time applications and scalable AI systems combined with explainable solutions will have a vital function for dermatological healthcare in the upcoming years.

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