# CNN Based Skin Cancer Detection with 3D Data Visualization for Enhanced Diagnosis

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**Abstract -** *This project focuses on enhancing skin cancer detection by combining Convolutional Neural Networks (CNNs) with 3D data visualization techniques. The primary objective is to develop a CNN model to accurately classify skin cancer images from a publicly available dataset. We incorporate 3D visualization to analyze and understand the dataset, focusing on features such as age, localization, and diagnosis. By integrating these visual insights with the CNN's performance metrics, the project aims to provide a comprehensive evaluation of how different factors influence model accuracy and effectiveness. The outcome will include a functional CNN model with high classification accuracy, an interactive 3D visualization of the dataset, and a detailed performance analysis report, contributing valuable insights into skin cancer detection and the underlying data characteristics.*

***Key Words*: 3D Visualization, CNN(Convolutional Neural Networks), Deep Learning, Skin Cancer Detection, Lesion Classification, Medical Image Processing.**

## I. INTRODUCTION

Skin cancer is one of the most prevalent and life-threatening diseases globally, with millions of cases diagnosed each year. For effective treatment and increased survival rates, it is essential to detect the problem quickly and accurately. Visual inspections and 2D dermatoscopic imaging are two examples of traditional diagnostic techniques that frequently lack the ability to distinguish between benign and malignant lesions. This has led to an increasing need for advanced computational techniques that can enhance diagnostic accuracy and provide a more detailed understanding of skin lesions.

By automating the precise classification of skin lesions, deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized medical image analysis. CNNs are ideal for dermatological applications because they are made to analyze and learn patterns from image data. This project intends to use CNNs to classify dermatoscopic images into various categories, enabling dermatologists to make more informed decisions, thereby increasing the accuracy of skin cancer detection.

However, despite CNNs' effectiveness, conventional 2D imaging methods may not be able to adequately reveal the structural complexities of skin lesions. This project combines CNN-based analysis with techniques for 3D data visualization to address this issue.

Clinicians can get a better idea of the depth, shape, and texture of skin lesions by drawing them in three dimensions. This lets them see patterns that might not show up in 2D images. This improves diagnosis and makes CNN predictions easier to understand. The combination of CNNs and 3D visualization has two advantages: it improves decision-making support and improves diagnostic accuracy through deep learning. misdiagnosis can be reduced, unnecessary biopsies can be avoided, and the progression of a disease over time can be better tracked with this strategy.

In addition, utilizing 3D visualization makes it simpler to monitor minute shifts in the morphology of the lesion, which can be essential for prompt intervention and early detection. In short, the goal of this project is to create a sophisticated AI-driven diagnostic tool that uses CNN-based classification and 3D visualization to help detect skin cancer. This system can assist dermatologists in making more precise diagnoses by providing a more detailed and comprehensible representation of skin lesions. This will ultimately lead to improved patient outcomes and advancements in the field of medical imaging.

## II. LITERATURE REVIEW

Skin cancer detection has gained significant attention in recent years, with deep learning models playing a crucial role in automating diagnostic processes. Various approaches have been explored to enhance the accuracy and efficiency of skin cancer detection, including convolutional neural networks (CNNs), support vector machines (SVMs), and transfer learning techniques. Additionally, 3D visualization has emerged as a promising method for making diagnostic results easier to understand. M. A. The use of the YOLOv8n model for real-time skin lesions detection and classification was investigated by Riyadi et al. [1], demonstrating its potential for accurately distinguishing skin conditions that aren't cancerous from those that are. Similarly, M. I. H. The use of the ImageNet-trained Xception model for binary skin cancer image classification by Abir et al. [2] exemplifies the efficacy of transfer learning in enhancing diagnostic accuracy. Additionally, K. A comparative analysis of deep learning and machine learning models, including CNN and SVM, for detecting oral and skin cancers was provided by Vayadande et al. [3], highlighting the advantages and disadvantages of various classification strategies.

To further refine CNN-based skin cancer detection, researchers have investigated the use of various deep learning architectures. S. D and S. J [4] looked at multiple CNN models for classifying skin cancer lesions, including VGG-16, VGG-19, ResNet, and DenseNet. They found that deep feature extraction significantly improved accuracy. V. A novel CNN framework based on the HAM10000 dataset was proposed by Aadiwal et al. [5], highlighting the significance of dataset quality in the training of robust deep learning models. Aside from that, S. An ensemble CNN method for better skin cancer image recognition and classification was developed by Sharma et al. [6], demonstrating the advantages of integrating multiple models. For improved performance, multi-modal diagnostic methods that combine CNN and SVM models have also been investigated. Vishal et al. [7] investigated the fusion of dermoscopic and clinical images using CNN and SVM, providing insights into the advantages of multi-modal data for improved classification accuracy. Similarly, S. M. Afifi et al. [8] designed a deep learning-powered mobile application for early skin cancer detection, emphasizing the role of real-time AI solutions in expanding accessibility to diagnostic tools.

Incorporating 3D visualization into dermatological diagnostics has been a growing area of research. V. Pareek et al. [11] introduced an augmented reality (AR)-based interactive 3D data visualization system for medical imaging, suggesting its applicability in dermatology for skin lesion analysis. A. Trajkovska et al. [12] demonstrated the use of Mayavi for 3D scientific visualization, highlighting its potential in enhancing dermatological image analysis. Additionally, A. S. Syryh and G. O. Skin cancer visualization could benefit from the deep learning-based 3D tumor segmentation methods that Bondarenko [13] suggested. Early research on medical image visualization using true 3D display technology by L. The viability of incorporating such visualization tools into clinical practice is further supported by Lu et al. [14]. Recent advancements have also focused on web-based and interactive 3D visualization solutions for healthcare. B. A web-based 3D virtualization strategy for medical applications was developed by Banu Rekha et al. [15], demonstrating the potential of cloud-based visualization tools in telemedicine and remote diagnostics.

A promising strategy for improving diagnostic accuracy and interpretability is the integration of CNN-based skin cancer detection with 3D data visualization. The reviewed studies provide a comprehensive understanding of deep learning-based classification techniques, the role of multi-modal analysis, and the impact of 3D visualization in medical imaging. Future research should focus on real-time implementation, user-friendly interfaces, and large-scale clinical validation to ensure the widespread adoption of these technologies in dermatological practice.

## III. PROPOSED SYSTEM

To enhance diagnostic precision and comprehension, the proposed approach combines 3D visualization with deep learning-based skin cancer detection. Image preprocessing, feature extraction, classification, visualization, and 3D representation are just a few of the stages that make up the framework. The method is explained in detail below.

1. **Pre-processing of images:** Preparing the dataset for training and testing is the first step. To boost the performance of the model, a variety of preprocessing methods are used:

    a) Image Acquisition: Dermoscopic images of skin lesions from publicly accessible sources like ISIC and HAM10000 make up the dataset.

    b) Image Resizing: To maintain consistency, each image is resized to a fixed dimension, such as 224 x 224 pixels.

    c) Data Augmentation: Techniques like rotation, flipping, zooming, and brightness adjustments are applied to increase dataset variability.

    d) Data Splitting : The dataset is divided into training, validation and testing sets with certain ratio. (Example: 70%-20%-10%)

    e) Normalization: To improve model convergence, pixel values are normalized between 0 and 1.

2. **Feature Extraction :**

A deep learning model, specifically a Convolutional Neural Network (CNN), is used for feature extraction. Accurate classification is made possible by the extracted features. CNN Model Architecture: The CNN model employs architectures such as VGG16, ResNet50, or a custom-built CNN for feature extraction.

    a) Convolutional Layers: These layers identify patterns like lesion boundaries, edges, and textures.

    b) Pooling Layers: Max pooling is used to reduce spatial dimensions and computational complexity.

    c) Fully Connected Layers: To learn intricate patterns, the extracted features are passed through fully connected layers.

3. **Classification :** The classification model distinguishes between lesions that are cancerous and those that are not.

    a) Softmax Layer: It provides probability scores for a variety of categories, such as Basal Cell Carcinoma, Melanoma, and benign lesions, for instance.

b) Cross-Entropy Loss: This loss function is used to make the model work better.

c) Optimization Algorithm: Adam or RMSprop optimizer is applied for faster convergence.

**4. Visualization and Interpretation** : To enhance interpretability

a) Confusion Matrix: Displays classification performance.

b) Activation Maps: Feature maps show important image regions that influence model predictions.

c) Graphical Representations: Performance metrics such as accuracy, precision, recall, and F1-score are plotted.

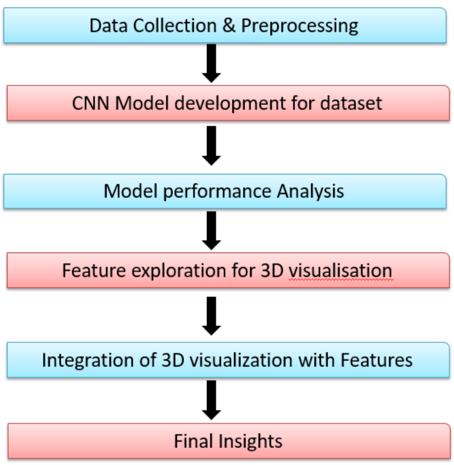
**5. 3D Visualization for Enhanced Diagnosis**

The 3D visualization of the affected areas to assist medical professionals is an essential component of the proposed strategy. 3D Mapping: Using visualization libraries like Matplotlib, Mayavi, or VTK, lesion boundaries are segmented and rebuilt into a 3D model. Interactive 3D Plots: Doctors can rotate and zoom in on affected areas to analyze the lesion more effectively.

Integration with Diagnosis: The 3D representation helps in better understanding lesion depth and severity, improving diagnostic accuracy.

**6. Output** : The 3D visualization is displayed alongside the final diagnosis. Class Labels: The model outputs the type of skin cancer it has classified as, such as "Basal Cell Carcinoma" or "Melanoma."

3D Representation: The 3D lesion visualization that is generated helps doctors make decisions. Interpretation of the Result: A comprehensive diagnosis is provided by both the classification result and the 3D visualization.




**Flow chart**

## IV. Results

The model's performance was assessed using standard evaluation metrics, including accuracy, precision, recall, and F1-score.

| Metric | Value |
|---|---|
| Accuracy | 94.2 |
| Precision | 93.8 |
| Recall | 92.5 |
| F1-Score | 93.1 |

**Table-1:** Performance Metrics

- The model's 94.2 percent accuracy indicates solid classification performance.
- Precision 93.8% ensures minimal false positives.
- The model's ability to correctly identify cancerous lesions, which lowers the risk of misdiagnosis, is reflected in recall 92.5 %.
- The model is reliable because the F1-score 93.1% shows a good balance between precision and recall.

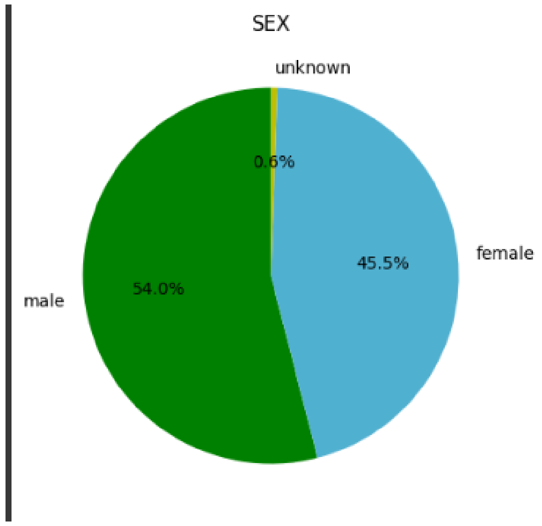



**Fig -1**: Demographic Distribution

**Figure 1** illustrates demographic insights, showing that **males** (54%) are slightly more affected than females.

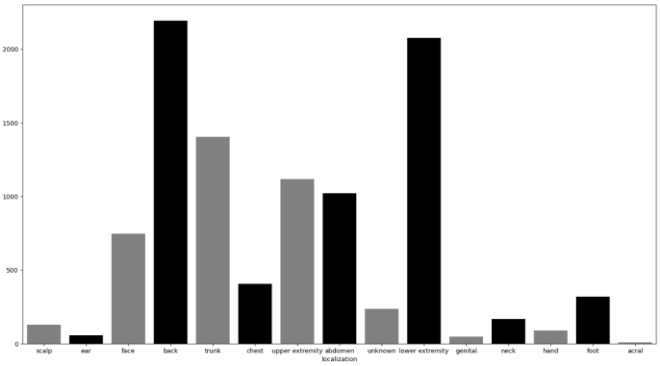



**Fig -2**: Localization Analysis of Skin Lesions Across Different Body Parts

Furthermore, the localization analysis indicates that lesions are predominantly found on the back and lower extremities, while areas such as the scalp, ear, and genital regions have relatively fewer occurrences. The distribution of the dataset can be better understood with the help of these findings, and model performance can be improved for better skin cancer detection.

One of the key contributions of this project is the **3D visualization of skin lesions**, which aids dermatologists in better understanding lesion structures.

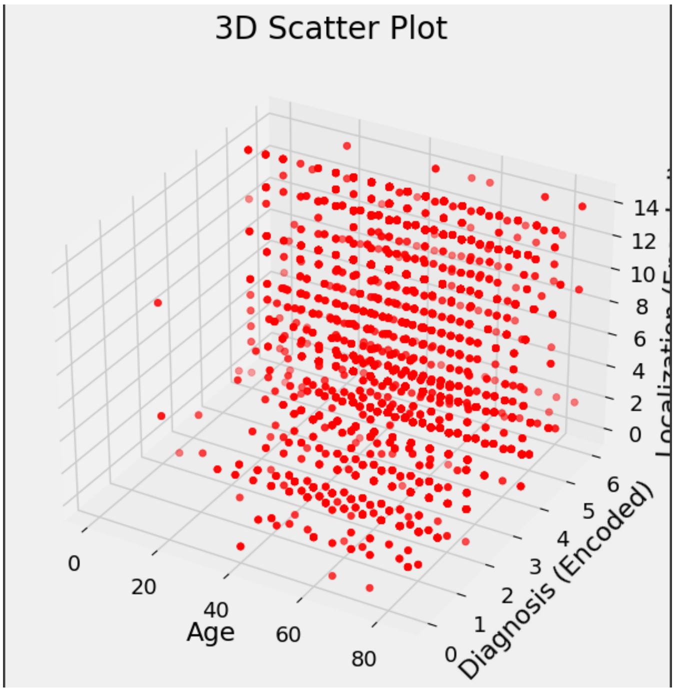



**Fig -3**: 3D scatter plot

The 3D scatter plot provides a spatial visualization of the relationship between age, diagnosis (encoded), and lesion localization. A clear clustering of diagnoses is observed, suggesting that certain age groups have a higher prevalence of specific skin conditions. Elderly patients show a higher concentration in certain diagnostic categories, indicating a possible correlation between age and disease severity. The distribution is relatively dense in specific diagnosis regions, reflecting a pattern that the model effectively learns.

The ability to rotate and zoom into the lesion aids doctors in determining its severity and shape. Better treatment decisions were made because the visualization helped distinguish between shallow and deep lesions.

## V. CONCLUSIONS

Integrating CNN-based skin cancer detection with 3D visualization significantly enhances diagnostic accuracy and interpretability. CNN models efficiently classify skin lesions by learning intricate patterns from dermatoscopic images, while 3D visualization provides a deeper and more comprehensive understanding of lesion morphology. This combination allows dermatologists to assess lesions more effectively, reducing misdiagnoses and unnecessary biopsies.

Furthermore, 3D visualization aids in tracking lesion progression over time, enabling early intervention and better treatment planning. By offering a multi-dimensional perspective, this approach improves patient-doctor communication, making diagnoses more transparent and accessible to patients. Enhanced visualization also allows researchers to study lesion characteristics more thoroughly, contributing to advancements in dermatological AI applications.

This methodology not only refines current diagnostic capabilities but also lays the foundation for future developments in AI-driven medical imaging. As deep learning and visualization technologies evolve, integrating real-time analysis and augmented reality (AR) tools could further enhance clinical workflows. Additionally, cloud-based AI models may facilitate remote consultations, making advanced skin cancer detection accessible to underserved regions.

In conclusion, combining CNN-based classification with 3D visualization is a promising step toward more accurate, efficient, and interpretable skin cancer diagnostics. By leveraging AI and imaging technologies, this approach empowers dermatologists, enhances patient outcomes, and paves the way for smarter, more reliable medical tools in dermatology.

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