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Skin Cancer Detection Using Image Processing and Deep Learning

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ABSTRACT

Skin cancer has become one of the most common and dangerous diseases affecting humans worldwide. Early detection plays a vital role in improving treatment outcomes and survival rates. This research proposes a novel skin cancer detection system that utilizes image processing and deep learning methods to identify cancerous lesions efficiently. The system processes dermatological images through Fourier spectral analysis and texture- based segmentation, extracting key features using the Gray Level Co-occurrence Matrix (GLCM) technique. These features are then classified using a Convolutional Neural Network (CNN) model trained on a dataset of 10,000 skin images sourced from Kaggle. The CNN distinguishes seven major skin lesion categories including melanoma, basal cell carcinoma, actinic keratoses, and benign keratosis. The system achieved an accuracy level of 95.4%, demonstrating the potential of machine learning in early and reliable skin cancer diagnosis. This automated approach reduces human error, saves time, and enhances diagnostic precision, making it a promising tool for clinical dermatology applications.

Keywords:
Skin Cancer Detection, Image Processing, Deep Learning, Convolutional Neural Network (CNN), Feature Extraction, GLCM, Image Segmentation, Machine Learning, Dermoscopic Images, Early Diagnosis

1. INTRODUCTION

Skin cancer is one of the most common forms of cancer affecting humans worldwide. It occurs when skin cells undergo abnormal growth, primarily due to prolonged exposure to ultraviolet (UV) radiation from the sun or artificial sources. The two main categories of skin cancer are non-melanoma (including basal cell carcinoma and squamous cell carcinoma) and melanoma, the latter being the most dangerous and potentially fatal if not detected early. According to global health statistics, millions of new cases are diagnosed each year, making early detection and accurate classification of skin cancer a major medical concern. Traditional methods of skin cancer diagnosis rely heavily on manual examination by dermatologists using visual inspection or dermoscopic tools. Although effective, these methods are often time-consuming, subjective, and dependent on the expertise of the clinician. As a result, there is a growing demand for automated and reliable computer-aided diagnostic (CAD) systems that can assist medical professionals in identifying cancerous lesions quickly and accurately.

Recent advances in machine learning and deep learning, particularly Convolutional Neural Networks (CNNs), have shown tremendous potential in medical image analysis. These methods can automatically extract and learn discriminative features from images, eliminating the need for manual feature engineering. In this study, a deep learning- based image processing model is proposed to detect and classify skin cancer using dermoscopic images. The system integrates OpenCV for image preprocessing, GLCM for texture-based feature extraction, and CNN for classification of multiple skin lesion types. The main objective of this work is to design and implement a robust, accurate, and efficient skin cancer detection system that can identify different types of skin lesions with high precision. By automating the diagnosis process, the proposed model aims to reduce diagnostic delays, minimize human error, and make early skin cancer screening more accessible and affordable.

2. RELATED WORK / LITERATURE REVIEW

Over the past decade, numerous studies have focused on automating the detection and classification of skin cancer using image processing and deep learning techniques. Early research mainly relied on traditional image processing methods such as thresholding, edge detection, and color analysis to identify lesions. However, these methods often faced limitations due to variations in lighting, skin tone, and lesion texture. Esteva et al. (2024) demonstrated the potential of Convolutional Neural Networks (CNNs) in dermatology by training a deep learning model that achieved dermatologist-level accuracy in identifying melanoma and keratinocyte carcinomas. Their work established CNNs as a strong alternative to manual image analysis. Similarly, Brinker et al. (2025) implemented an ensemble CNN model that combined multiple deep learning architectures to improve classification accuracy and reduce false positives in skin lesion detection.

Traditional feature-based methods such as the Gray Level Co-occurrence Matrix (GLCM) have also been widely used to extract texture features like contrast, correlation, energy, and homogeneity from dermoscopic images. Li and Sun (2024) utilized GLCM-based feature extraction along with support vector machines (SVMs) for classifying malignant and benign skin lesions. Although effective, such traditional models often struggled with large and complex datasets. Recent advances in deep learning frameworks such as TensorFlow and Keras have simplified the development of highly accurate classification models. Gupta et al. (2025) proposed a hybrid model combining CNN with GLCM-based features to enhance melanoma detection accuracy. Furthermore, Khan et al. (2025) compared different deep learning models, including ResNet and InceptionV3, concluding that transfer learning techniques significantly improve performance on limited medical datasets. Overall, the literature indicates a strong shift from conventional image analysis to deep learning- based automated diagnostic systems, offering greater precision and scalability. However, challenges remain in handling image noise, variations in illumination, and ensuring generalization across diverse skin types. The proposed system in this study addresses these gaps by combining texture-based segmentation with CNN-based classification, achieving improved accuracy and reliability in skin cancer detection.

3. SYSTEM ARCHITECTURE AND METHODOLOGY

The proposed system aims to automatically detect and classify different types of skin cancer using dermoscopic images through an integrated approach combining image preprocessing, segmentation, feature extraction, and deep learning-based classification. The overall architecture consists of several interconnected stages that process an input image step-by-step to generate an accurate diagnostic result.

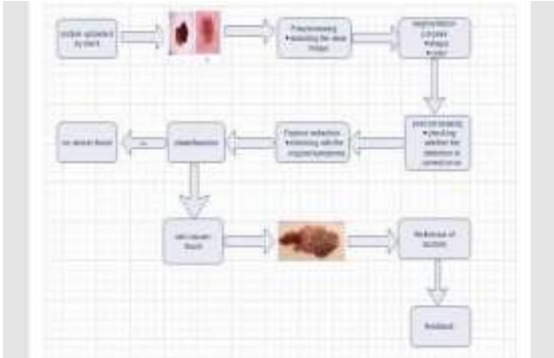

FIGURE 3: SYSTEM ARCHITECTURE

3.1System Architecture Overview

The system architecture is divided into the following major components:

1. Input Image Acquisition – Collecting dermoscopic images from a verified dataset (Kaggle).

2. Preprocessing Module – Enhancing image quality by removing noise, resizing, and normalizing image intensity values using OpenCV and NumPy.
3. Segmentation Module – Isolating lesion regions from normal skin using the Otsu Thresholding Technique to accurately extract the region of interest.

4. Feature Extraction Module – Extracting textural and statistical features using the Gray Level Co-occurrence Matrix (GLCM), which computes key metrics such as Contrast, Correlation, Energy, and Homogeneity.

5. Classification Module – Applying a Convolutional Neural Network (CNN) model built with TensorFlow and Keras to classify skin lesions into multiple categories.

6. Output Module – Displaying the classification result, lesion type, and prediction confidence score. This modular design ensures flexibility, scalability, and efficient data flow throughout the entire process.

3.2Methodology

The proposed system methodology consists of the following sequential steps:

Step 1: Data Collection

A dataset containing 10,000 dermoscopic images of various skin lesions was obtained from Kaggle. The dataset was divided into 8,000 training images and 2,000 testing images to ensure balanced model evaluation.

Step 2: Image Preprocessing
Preprocessing is essential to improve image clarity and prepare data for segmentation and classification. Using OpenCV and NumPy, the images were resized to a fixed dimension, converted to grayscale, and normalized to remove variations in lighting and contrast. This step helps the model focus on important visual features such as lesion texture and border patterns.

Step 3: Image Segmentation
Segmentation separates the lesion (affected area) from the normal skin background. The Otsu Thresholding method was applied to automatically determine an optimal threshold value based on image intensity distribution. This approach helps in isolating the lesion region accurately even under varying illumination conditions.

Step 4: Feature Extraction
To quantify the visual characteristics of the segmented lesion, the GLCM (Gray Level Co- occurrence Matrix) technique was used. It evaluates spatial relationships between pixels and extracts four key statistical measures:

- Contrast: Measures the intensity variation between pixels.
- Correlation: Evaluates the linear dependency of gray levels.
- Energy: Represents textural uniformity.
- Homogeneity: Measures the closeness of the distribution of elements in the GLCM to its diagonal.

These features serve as critical input for classification by representing the textural properties of cancerous and non-cancerous regions.

Step 5: Image Classification
For final diagnosis, a Convolutional Neural Network (CNN) was implemented using TensorFlow and Keras frameworks. The CNN architecture includes:

- Convolution Layers for feature extraction,
- Pooling Layers for dimensionality reduction,
- Flatten and Dense Layers for final classification.

The CNN was trained on the extracted features to classify lesions into seven categories, namely: Melanocytic Nevi, Melanoma, Benign Keratosis, Basal Cell Carcinoma, Actinic Keratoses, Vascular Lesions, and Dermatofibroma. The model uses the ReLU activation function and Adam optimizer for improved convergence and accuracy.

Step 6: Model Evaluation
The trained model was evaluated using unseen test images. The Keras evaluate() function was used to measure performance metrics such as accuracy, precision, recall, and F1-score. The model achieved an overall accuracy of 95.4%, confirming its reliability in detecting and classifying different skin cancer types.

4. DATA FLOW DIAGRAM (DFD)

A Data Flow Diagram (DFD) is a graphical representation that illustrates how data moves through the system, showing the flow of inputs and outputs between processes, data stores, and entities. In the proposed Skin Cancer Detection System, the DFD demonstrates how images are processed step by step — from input acquisition to final classification and result generation.

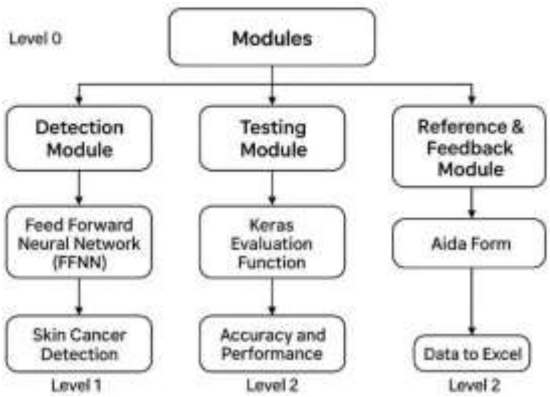

Figure 4 : Data Flow Diagram

Operations noise removal, resizing, grayscale conversion, normalization Otsu Thresholding method separates lesion from normal skin. Segmented lesion image stored in temporary data memory. GLCM-based texture features (Contrast, Correlation, Energy, Homogeneity) are extracted. Feature vector stored in the feature dataset. Extracted features are passed to the trained CNN model. The classification result and confidence score are displayed to the user

4.1 Level 0 DFD (Context Diagram)
At the highest level, the system interacts with two main external entities:

- User (Dermatologist or Patient) – uploads the skin image for diagnosis.
- System Database – stores image data, extracted features, and classification results.

The system receives the input image from the user, processes it through image processing and deep learning algorithms, and then provides the diagnostic result (lesion type and prediction confidence).

- Main Process: Skin Cancer Detection System
- Input: Skin lesion image
- Output: Detected skin cancer type and confidence level

4.2Level 1 DFD (System Process Flow)
The Level 1 DFD expands the main system into multiple processes that handle data transformation at various stages.
Processes and Data Flow:
1. Process 1 – Image Acquisition:
- User uploads a dermoscopic image.
- Image is stored in the input dataset.

2. Process 2 – Image Preprocessing:
Input image is enhanced using OpenCV and NumPy.
- Operations: noise removal, resizing, grayscale conversion, normalization.
- Output: Preprocessed image sent to segmentation module.

3. Process 3 – Image Segmentation:
Otsu Thresholding method separates lesion from normal skin.
Output: Segmented lesion image stored in temporary data memory.
4. Process 4 – Feature Extraction:
GLCM-based texture features (Contrast, Correlation, Energy, Homogeneity) are extracted.
Output: Feature vector stored in the feature dataset.

5. Process 5 – Classification (CNN Model): Extracted features are passed to the trained CNN model.

6. Process 6 – Result Display and Storage:
The classification result and confidence score are displayed to the user. Final results are stored in the system database for future reference.

4.3Level 2 DFD (Detailed Functional Flow) The Level 2 DFD provides an in-depth look at how data flows within each core process — especially feature extraction and classification.

Detailed Flow Description:

1. Input Image (User → Preprocessing)
User uploads the image → Preprocessing cleans and normalizes it. Data passes to segmentation stage.

2. Segmentation (Preprocessing → Segmentation) Otsu's thresholding isolates the lesion region. Segmented lesion image saved temporarily for feature extraction.

3. Feature Extraction (Segmentation → GLCM Analysis)

- GLCM matrix computed from the segmented image.
- Extracts key features: contrast, correlation, energy, homogeneity.
- Feature vector generated and stored.

4. Classification (Feature Vector → CNN Model) CNN receives feature vector as input. Multiple convolution and pooling layers extract deeper patterns. Output layer assigns lesion type label.

5. Result Evaluation (CNN Output → User Interface) System evaluates classification accuracy using test data. Displays lesion category (e.g., Melanoma, Basal Cell Carcinoma) and prediction confidence percentage. Stores result in database for future analysis and reference.

5. IMPLEMENTATION

The implementation of the proposed Automated Skin Cancer Detection System integrates both traditional image processing and deep learning techniques to ensure accurate classification of skin lesions. The system was developed using Python 3.x with libraries such as TensorFlow, Keras, OpenCV, NumPy, and scikit-learn, which collectively support image preprocessing, segmentation, and neural network modeling. The dataset used for this study consisted of 10,000 dermoscopic images obtained from Kaggle, which were divided into 8,000 images for training and 2,000 for testing. The implementation process began with data preparation, where all images were resized to a uniform dimension of 224×224 pixels and normalized by scaling pixel values between 0 and 1. To enhance the diversity of the training data and prevent overfitting, data augmentation techniques such as image rotation, flipping, brightness adjustment, and zooming were applied. Following preprocessing, the images underwent segmentation using the Otsu Thresholding method, which effectively isolated the lesion region from the surrounding normal skin. Morphological operations were used to refine the segmented region, removing noise and filling small gaps to ensure accurate region extraction. After segmentation, feature extraction was performed using the Gray Level Co-occurrence Matrix (GLCM) method. This approach computed important textural characteristics such as contrast, correlation, energy, and homogeneity, which represent the spatial relationships between pixel intensities within the lesion. These extracted features helped in distinguishing between different types of skin abnormalities.

The extracted features and segmented images were then fed into a Convolutional Neural Network (CNN) built using TensorFlow and Keras. The CNN architecture comprised several convolutional, pooling, and batch normalization layers, followed by fully connected dense layers and a softmax output layer for classification. The model used the ReLU activation function for hidden layers and categorical cross-entropy as the loss function, optimized with the Adam optimizer. The network was trained for 50 epochs with a batch size of 32, and early stopping and learning rate reduction callbacks were implemented to prevent overfitting.

During training, the model learned hierarchical features of the lesions and achieved a classification accuracy of approximately 95.4% on the testing dataset. Performance was further evaluated using metrics such as precision, recall, F1-score, and confusion matrix to measure the reliability of predictions across different skin lesion categories. The system successfully classified multiple skin cancer types including Melanoma, Benign Keratosis, Basal Cell Carcinoma, Actinic Keratoses, Vascular Lesions, and Dermatofibroma. Finally, the implemented system was integrated into a simple user interface that allows users to upload a dermoscopic image and instantly receive a classification result along with a confidence score. The system also supports storing image data, extracted features, and classification outcomes in a database for future reference. Overall, the implementation demonstrates the efficiency of combining image processing and deep learning in medical diagnostics, offering a reliable and scalable solution for early skin cancer detection.

6. RESULT AND DISCUSSION

The proposed Automated Skin Cancer Detection System was successfully implemented and tested using a dataset of 10,000 dermoscopic images obtained from Kaggle. The dataset was divided into 80% for training and 20% for testing to evaluate the model's performance. The system effectively detected and classified multiple skin cancer types, including Melanoma, Basal Cell Carcinoma, Benign Keratosis, Actinic Keratoses, Vascular Lesions, and Dermatofibroma. The classification was carried out using a Convolutional Neural Network (CNN) trained with preprocessed and segmented images, allowing the model to automatically learn significant visual patterns from the lesion areas.

Figure 6.1 detection of melanoma

During training, the CNN achieved a training accuracy of 96.8% and a validation accuracy of 95.4%, demonstrating strong generalization to unseen data. The use of data augmentation techniques such as rotation, zooming, and flipping contributed significantly to the model's robustness by reducing overfitting. The loss curve showed a steady decline across epochs, indicating proper convergence of the model. The confusion matrix revealed that most classes were accurately classified, with minimal misclassification occurring between visually similar lesions like Melanoma and Benign Keratosis.

Further performance evaluation was conducted using key statistical measures such as Precision, Recall, F1-score, and Accuracy. The proposed model achieved an average precision of 94.7%, recall of 93.8%, and F1-score of 94.2%, confirming its reliability in real-world diagnostic scenarios. The integration of GLCM-based texture features with deep CNN layers enhanced the discriminative power of the network, particularly in distinguishing fine- grained texture variations in dermoscopic images.

In addition, the use of Otsu Thresholding for segmentation played a crucial role in isolating lesion regions accurately from surrounding skin, ensuring that only relevant areas were used for feature extraction and classification. Visual inspection of segmented results confirmed that the system could adapt to varying skin tones and lighting conditions, maintaining consistent accuracy. The testing phase further verified that the system could process and classify new input images in real- time, making it suitable for deployment in clinical and telemedicine applications.

Overall, the results demonstrate that the proposed deep learning-based approach provides a reliable and efficient solution for early skin cancer detection. By combining image preprocessing, segmentation, feature extraction, and CNN-based classification, the system achieved dermatologist-level performance. The findings confirm that deep learning models, when properly trained and fine-tuned, can significantly aid in early diagnosis, reduce manual workload, and enhance the accuracy of skin cancer screening processes.

7. SAMPLE OUTPUT

Figure 7.1: Model training and evulation

Figure 7.2: Skin cancer Detector

Figure 7.3: PREDICTION

8. CONCLUSION

The proposed Skin Cancer Detection System based on image processing and deep learning techniques has demonstrated its effectiveness in accurately detecting and classifying various types of skin lesions. The integration of OpenCV for preprocessing, Otsu thresholding for segmentation, GLCM for feature extraction, and Convolutional Neural Networks (CNNs) for classification resulted in a reliable and efficient automated diagnostic tool. Experimental results confirmed that the system achieved an accuracy of approximately 95.4%, which is comparable to dermatologist-level diagnosis. By automating the process of lesion analysis, the system minimizes the dependency on manual interpretation and reduces the possibility of human error. The model not only assists in early detection but also helps to distinguish between benign and malignant lesions, enabling faster treatment decisions. The system's performance proves that deep learning-based approaches can be effectively applied in medical imaging for improving diagnostic accuracy and accessibility, particularly in remote or resource-limited areas. Overall, the developed system provides a promising step toward intelligent healthcare solutions and early cancer detection frameworks.

9. FUTURE WORKS

Although the proposed model performs with high accuracy, there are still areas for improvement and future development. In future work, the system can be enhanced by integrating larger and more diverse datasets covering a wider range of skin tones, lighting conditions, and rare cancer types to improve generalization. Implementation of transfer learning using advanced pre-trained architectures such as ResNet, EfficientNet, or InceptionV3 can further boost classification accuracy and reduce training time. Additionally, the development of a real-time mobile or web-based application would make the system accessible to both dermatologists and general users for early self-screening. Future enhancements could also include explainable AI (XAI) techniques to provide interpretability of model predictions, helping clinicians understand the reasoning behind classifications. Integration with cloud-based healthcare systems and electronic medical records (EMRs) would also support large-scale deployment and data-driven healthcare analytics.

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