

SkinDX: Skin Cancer Detection Using CNN

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Abstract - Skin cancer is one of the most common types of cancer in the world. Early detection is very important for treatment to work. This paper describes a method for automatically finding skin cancer using Convolutional Neural Networks (CNNs) that is based on deep learning. The proposed system employs transfer learning in conjunction with preprocessing methods, including image normalisation and data augmentation, to enhance model performance and generalisation. To help people understand better, an attention mechanism is added to help people focus on important lesion areas, and Grad-CAM is used to give visual explanations. The model is tested on standard dermoscopic image datasets and gets high marks for accuracy, sensitivity, and specificity. Also, a lightweight web-based interface is made for making predictions in real time. The proposed system can help dermatologists make better clinical decisions and find problems earlier.

Key Words: Skin Cancer Detection, Deep Learning, CNN, Transfer Learning, Attention Mechanism, Grad-CAM, Dermoscopic Images, Medical Image Analysis

1. INTRODUCTION

Skin cancer is one of the most common and fastest-growing types of cancer in the world. It is mostly caused by being exposed to UV radiation for a long time. Finding the disease early is very important for effective treatment and greatly increases the chances of survival for patients. But traditional ways of diagnosing, like dermatologists looking at the skin with their eyes and using a dermoscope, can take a long time, be subjective, and depend on the doctor's experience. This could cause differences in diagnosis and delays in treatment, especially in areas where it's hard to get to specialists. In the last few years, improvements in deep learning and artificial intelligence have led to promising ways to automatically analyse medical images. Convolutional Neural Networks (CNNs) have shown great results in image classification tasks because they can learn complex visual features like color, shape, and texture. Transfer learning techniques improve model performance even more by using networks that have already been trained.

This makes them work well even with small datasets. Even though these improvements have been made, there are still problems like data imbalance, lack of interpretability, and the need for real-time deployment. This research proposes a CNN-based skin cancer detection system that uses preprocessing methods like image normalisation and data augmentation to solve these problems. An attention mechanism is added to focus on the most important lesion areas, which makes classification more accurate. Grad-CAM is also used to give visual explanations, which makes the model more clear. The system is set up through a simple web interface that lets dermatologists make real-time predictions, which helps them make early diagnoses and clinical decisions.

2. LITERATURE SURVEY

1) The CNN + Transformer Hybrid Model (2023) combined EfficientNet with Vision Transformers to capture both local and global features, making it better at classifying things.

2) Tai et al. (2023) put forth an attention-based deep learning model employing self-attention mechanisms, which improved both efficiency and accuracy in the classification of skin lesions.

3) Kavitha et al. (2024) showed that CNN-based classification works well for telling apart small differences between skin lesions, with a high level of accuracy.

4) The use of CNNs along with transfer learning and GANs for class imbalance was suggested by Akinrinade et al. (2025). They generated more training samples which helped in increasing accuracy in early detection.

3. METHODOLOGY

The SkinDX system follows an ordered methodology for the detection of skin diseases using deep learning. The procedure begins with the user uploading a dermoscopic skin image via a web interface which serves as the input to the system. Several image preprocessing steps, including contrast enhancement, converting from RGB to binary, and binary conversion, are performed on the uploaded skin image to provide an image with better quality and distinguishable regions. Moreover, an edge

detection algorithm is used for tracing and determining boundaries of a skin lesion. Segmentation is then executed to segment the infected skin region from the rest of the image and in this way the infected skin portion alone will be selected for analysis. Extracting features using CNN can be effectively done from skin image as they can automatically learn complex features such as shape, texture, and color and then GLCM is used for extracting texture-based features. After obtaining the extracted features, the CNN classifier is used for training and it classifies the images into respective classes such as melanoma, eczema or normal skin. The outputs generated from the CNN classifier and the confidence value of a given image are predicted. Lastly, these results are presented through a Flask web interface and the information will also be saved in a database to generate a report for the users.

4. SYSTEM OVERVIEW

The proposed SkinDX is to develop an automatic and faster system of skin disease detection and classification based on the deep learning algorithm. In this system, user upload the dermoscopic images in the web interface provided. Image processing and machine learning algorithm are utilized to extract the relevant information (feature extraction) from images and classify skin diseases. It consists of preprocessing, feature extraction, and classification components integrated into one system; It minimizes human effort, speedup diagnostic process and improve the accuracy; Displayed with real-time results and accuracy score and saved in a database for tracking usage and accuracy with appropriate access security.

4.1 Image Preprocessing:

The system initially takes skin image as input. Image preprocessing includes resize, contrast enhancement, convert RGB, normalization. Noise reduction technique applied for the image improvement. Input image quality are improved and the performance of the model increase by this way.

4.2 Feature Extraction and Segmentation:

Edge detection and segmentation are the next steps after pre-processing, in order to separate the abnormal skin area from the background. Following this step, the extracted features will be obtained using the Convolutional Neural Network (CNN) which automatically learns the required features, like the texture, the shape and color changes; Gray Level Co-occurrence Matrix (GLCM) also used to calculate the texture based features and increase precision.

4.3 Classification and Result Generation:

Extracted features are fed into a pre-trained CNN model which then classifies the image as either melanoma, eczema or normal skin with appropriate confidences. Predictions are returned with confidences. This output is

then rendered to the user via a web-interface using Flask and stored in a database for report generation.

4.4 SYSTEM ARCHITECTURE

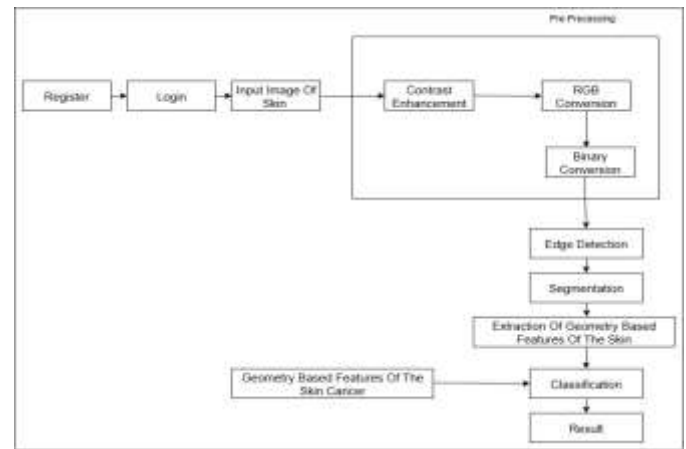


Fig No. 4.4: System Architecture

5. MODELING AND ANALYSIS:

The suggested system called SkinDX uses a methodical deep learning-based procedure in the process of diagnosing and categorizing the skin diseases from dermoscopic images. In the modeling process, input will be provided from user side, where the skin image will be uploaded from the web page. The image fed as an input would be initially pre-processed using methods such as re-sizing, contrast enhancement, normalization and noise removing in order to get high quality and standardize the images. The processed image is later fed to segmentation and edge detection to segment out the area of concern that is affected skin. The features from the input image is extracted using Convolutional Neural Network (CNN) which identifies the visual features in the image such as texture, shape, color variation. Gray Level Co-occurrence Matrix (GLCM) will also be utilized to detect the textural features. The features extracted from the image will be then fed into trained CNN classifier where, the input image will be classified into the types of disease such as melanoma, eczema, normal skin, etc. The image classification model will be trained on labeled data sets with optimized loss functions and optimization algorithms. The model evaluation is carried out using metrics like accuracy, sensitivity, specificity, loss curves, etc. The result from this evaluation suggests the dependable predictions from the model. The classified output will be displayed to the user through the web interface with confidence level.

The following describes the suggested FaceTrace workflow:

1. Image Input: The user uploads a skin image taken with a dermoscope via a web interface. This is the input to the system.
2. Preprocessing: The image fed is preprocessed by resizing, contrast enhancement, RGB conversion and normalization to enhance image quality.
3. Edge Detection: Skin lesion boundaries are identified using edge detection methods, helping to define the regions.
4. Segmentation: To have attention just on the interesting regions the system must differentiate the affected skin from the background.
5. Feature Extraction: CNN and GLCM method is used to extract the important features like texture, shape and color variations.
6. Classification: The features obtained above are then fed to a trained CNN which determines what category the image belongs to: Melanoma, Eczema, or Normal Skin.
7. Result Generation: The prediction and confidence levels are produced by the system.
8. Output Display: The final result will then be show to the user via a web page, and stored in a database.

6. RESULTS AND DISCUSSION

Proposed SkinDX system to detect and classify skin diseases from dermoscopic images was validated for the same. The web interface was developed and provided the image upload, image analysis, and prediction results in real time.

The system performed well in the following tasks:

- **Classification Accuracy:** The CNN based model classifies skin diseases like melanoma, eczema and normal skin properly. Through the effective pre-processing and feature extraction techniques the prediction accuracy is enhanced.
- **Detection Efficiency:** Provides quick and real time prediction so the time for human diagnosis is minimized thus the efficiency is improved.
- **System Usability:** The application has an easy to use interface where images can be uploaded, the results can be seen, and reports can be generated.

6.1 OUTPUT

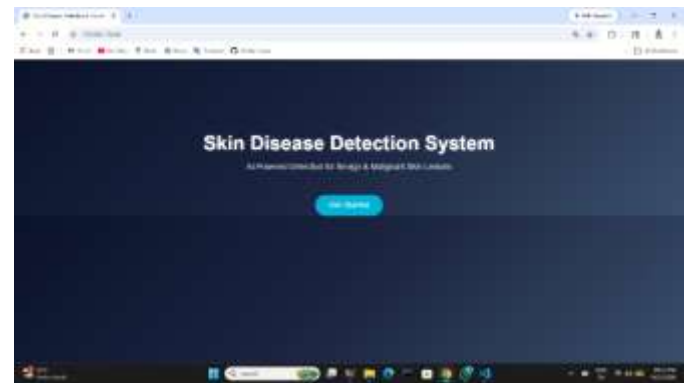


Fig. 6.1 Landing Page

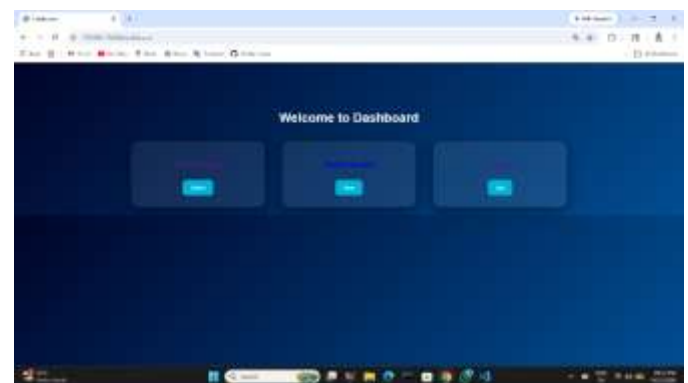


Fig 6.2 Dashboard

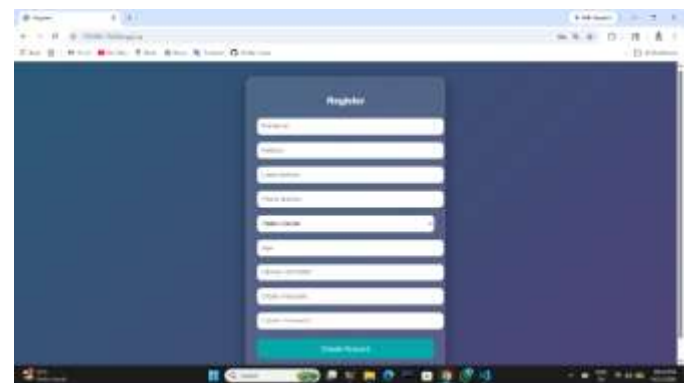


Fig 6.3 Registration Page

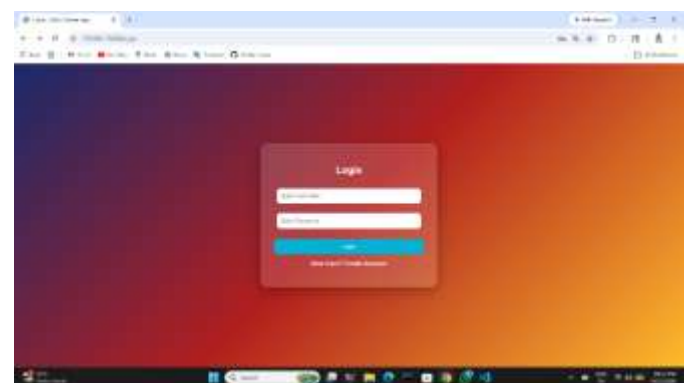


Fig 6.4 Login Page

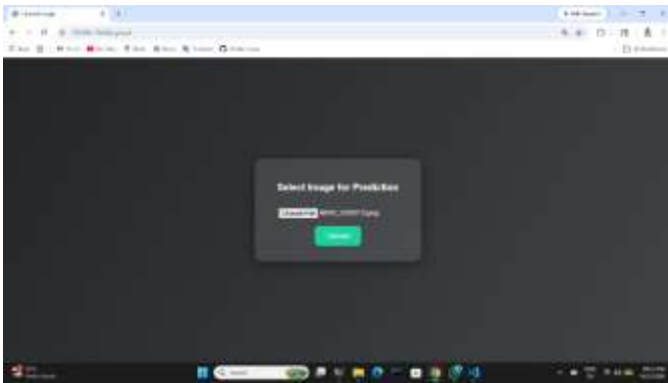


Fig 6.5 Upload Image as Input



Fig 6.6 Prediction Stage

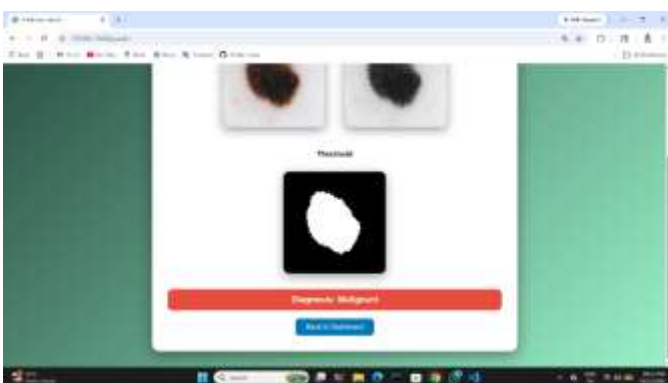


Fig 6.7 Output Displayed

7. FUTURE ENHANCEMENTS

The SkinDX system has potential to be upgraded with modern methods and increased functionality for real-world applications. Suggested improvements:

- **Improved Model Accuracy:** To achieve better results of the model, utilize the bigger datasets and more varied datasets.
- **Mobile App:** Mobile Application for real-time detection.
- **Explainable AI:** Added Grad-CAM. Now visualize better and understand what is happening

8. CHALLENGES

- **Data imbalance:** The performance and accuracy of the model is adversely affected by scarce and imbalanced data, where malignant examples are relatively fewer. Deep learning models will exhibit poor generalization on the less common cases and could potentially have very low prediction accuracies for that class.
- **Image Quality Variations:** The variation in lighting, resolution and noise of dermoscopic images could lead to ineffective pre-processing techniques and negatively influence prediction accuracies and feature extraction processes.
- **Model Interpretability:** Deep learning models are complex black-box entities, which does not provide easy explanations for decisions being made. This lowers the confidence in clinical settings of using such models.

9. CONCLUSION

SkinDX system illustrates an adequate framework for the automation of skin disease diagnosis through the utilization of deep learning algorithms. The combination of preprocessing, feature extraction, and CNN-based classification makes the system reliable. The availability of real-time predictions in the web interface enhance accessibility to the system.

10. REFERENCES

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