ISSN: 2348-1358

Impact Factor: 6.901

NAAS Rating: 3.77

A Cloud-Based Real-Time Skin Cancer Detection System Utilizing Artificial Intelligence

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Abstract:

One of the most serious types of cancer that can affect people is skin cancer. Skin cancer can be cured with early discovery, and the patient's life may be saved with the appropriate care. Skin cancer disorders come in a variety of forms, each with unique characteristics. Doctors utilize the ABCDET methodology, which is a classic method, to detect skin lesions. Nevertheless, with the number of cases of skin cancer rising worldwide in the present period, manual diagnosis of skin lesions is failing. To detect skin lesions more quickly and with fewer diagnostic errors, doctors' workloads can be reduced by using automatic skin lesion detection. Combining various deep learning and machine learning technologies can result in the development of an intelligent system that can correctly diagnose skin lesions.One type of deep learning model used to extract and classify skin lesion data is the neural network model. This work contains a real-time skin cancer detection simulation and compares CNN and random-forest classifiers for skin tumour categorization. The controversy centres on the HAM10000 the dataset, which contains pictures of seven distinct kinds of skin diseases. Following picture preparation for denoising and artifact removal, picture segmentation using Active Contours Without Edges (ACWE) and extraction of features using the ABCDT technique are performed. Next, a textural analysis is carried out using the Gray Level A combination Matrix (GLCM) and Fractal Dimensional Texture Analysis (FDTA).CNN's classification accuracy is 91.97%, whereas Random Forest's classification accuracy is 89.82%. The CNN model performed better than the Random Forest model for classification when the models that were trained were used in a simulation in real time to identify skin cancer.

Keywords—skin lesion, ABCDT, ACWE, GLCM, FDTA, CNN, random forest

I. Introduction

Given today's poor environmental conditions, humans are vulnerable to a variety of skin illnesses. High UV radiation exposure can damage skin DNA and cause abnormal cells that can lead to skin cancer. When a lesion grows quickly and spreads to other places of the skin, it is deemed malignant and should be treated as such. It is curable by surgically removing the afflicted part. In contrast, benign lesions grow throughout the affected area but do not spread quickly, making them less hazardous. Receiving medical assistance in the early stages of a tumour is critical for lowering mortality rates. In contrast to benign skin cancer, which includes benign keratosis-like (bkl), dermatofibroma (df), melanocytic nevi (nv), and vascular lesions (vasc), malignant skin cancer includes actinic keratoses, intraepithelial carcinoma (akiec), basal cell carcinoma (bcc), and melanoma. If the tumour is not removed, it has the potential to spread to other organs and tissues, ultimately killing the patient. Early identification of skin cancer can significantly lower the chance of death. Traditional procedures for diagnosing skin cancer include dermo copy and biopsy. A biopsy is an intrusive process that involves removing a sample of skin cancer from the body and sending it to a laboratory for investigation. After the related lab tests, the results will be determined; thus, skin cancer interpretation will take longer. Dermoscopy, on the other hand, is a non-invasive procedure that uses a magnifying lens to detect and evaluate skin cancer. Doctors must use a magnifying lens to closely examine the skin lesion and analyse it using the ABCDE method. This process takes a long time since specialists need to do a thorough examination and understand the skin problem. As the number of patients increases, the lengthy conventional methods become less successful in detecting skin cancer in a shorter period of time. As a result, it is vital to transition from manual to automated

M. Mohanedova *et al*, International Journal of Advances in Agricultural Science & Technology,
Vol.11 Issue.4, April 2024, pg. 24-30

ISSN: 2348-1358

Impact Factor: 6.901

NAAS Rating: 3.77

skin cancer detection. AI is widely recognized for its ability to reduce the workload of clinicians who must carefully monitor and analyse outcomes.Convolutional Neural Networks are one type of deep learning model that can be used to detect skin cancer through image categorization. The use of machine learning and deep learning models in the medical industry decreases diagnostic errors while simultaneously developing the field.

II. LITERATURESURVEY

H. Alquran et al. [4] developed a melanoma classification approach that combined an SVM classifier with Otsu's thresholding, ABCD feature extraction, and a Gray Level Co-occurrence Matrix (GLCM). Principal component analysis, or PCA, is used to choose characteristics. The results indicated 92.1% classification accuracy.

M. Vidya and M. V. Karki proposed a skin lesion classifier that distinguishes between benign and melanoma [6]. The technique makes use of the ABCD rule, GLCM, and HOG feature extraction. Geodesic Active Contour (GAC) is an active contour technique that was used to segment images. The classification was done using SVM, KNN, and Naïve Bayes classifiers. SVM outperformed the others with an accuracy of 97.8%.

Reference [8] provides a comparison of KNN, Decision Tree, and SVM classifiers for categorizing skin lesions. In the preparation stage, the Dull Razor algorithm was used to remove hair. The dermoscopic images were segmented using the ABCD feature extraction method and the mean-shift image segmentation algorithm. The relief approach is used to choose the features, while classifiers are utilized to categorize them. 78.2% proven to be the highest accuracy achieved using the SVM classification.

The authors of [9] described an automatic method for segmenting skin lesions. The method begins with noise and hair removal preprocessing, followed by picture segmentation using the GrabCut and Flood fill algorithms. Skin lesion classification is carried out utilizing k-means clustering. When tested on the PH2 and ISIC 2017 datasets, the suggested technique achieved an accuracy of 92% and 96%, respectively. The Dice coefficient values for the ISIC 2017 dataset are 0.82, but the PH2 dataset has them at 0.92.

III.SYSTEM ANALYSIS

A. EXISTING SYSTEM

Traditional procedures for diagnosing skin cancer[17] include dermoscopy and biopsy. A biopsy is an intrusive process that involves removing a sample of skin cancer from the body and sending it to a laboratory for investigation. After the related lab tests, the results will be determined; thus, skin cancer interpretation will take longer. Dermoscopy, on the other hand, is a non-invasive procedure that uses a magnifying lens to detect and evaluate skin cancer. Doctors must use a magnifying lens to closely examine the skin lesion and analyse it using the ABCDE method.

This process takes a long time since specialists need to do a thorough examination and understand the skin problem. As the number of patients increases, the lengthy conventional methods become less successful in detecting skin cancer in a shorter period of time. As a result, it is vital to transition from manual to automated skin cancer detection. AI is widely recognized for its ability to reduce the workload of clinicians who must carefully monitor and analyse outcomes. Deep learning algorithms, such as convolutional neural networks, can identify skin cancer through image classification. When deep learning and machine learning models of this type are introduced into the medical sector, the field progresses and diagnostic error rates fall.

DISADVANTAGES OF THE EXISTING SYSTEM

1. **Lack of Transparency:** Deep learning models, particularly CNNs, are commonly referred to as "black-box" models because humans find it difficult to read or comprehend how they make judgments. In medical settings, when practitioners need to know how a diagnosis was obtained, a lack of transparency can be problematic.

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2. Data Quality and Bias: The representativeness and quality of training data greatly influence how well AI models perform. Biases in training data, such as underrepresentation of specific demographic[16] groups or skin types, can lead to inaccurate or prejudiced predictions, exacerbating healthcare inequities.
3. Overreliance on Technology: Healthcare practitioners may become overly reliant on AI-based diagnostic technologies, reducing their awareness and critical thinking skills. Automated technologies should not totally replace clinical judgment; instead, they should be used as decision support tools.
4. Limited Generalization: AI models trained on certain datasets may not be as well-suited to handling novel or unknown circumstances. When dealing with rare or uncommon skin conditions, for example, that deviate significantly from the training data, they may not perform well.
5. Legal and Ethical Issues: Using AI to diagnose medical diseases raises legal and ethical difficulties, such as patient privacy concerns about the use of medical images, responsibility for diagnostic errors, and the need for informed consent for AI-assisted diagnosis.

B. PROPOSED SYSTEM

M. Vidya and M. V. Karki devised a skin lesion classifier that distinguishes between benign and melanoma. The technique makes use of the ABCD rule, GLCM, and HOG feature extraction. Geodesic Active Contour (GAC) is an active contour technique that was used to segment images. The classification was performed using SVM, KNN, and Naïve Bayes classifiers, with SVM achieving the highest accuracy of 97.8%.

The authors proposed an automatic method for segmenting skin lesions that begins with preprocessing for hair removal and noise, followed by picture segmentation using the GrabCut and Flood fill algorithms. Skin lesion classification is carried out utilizing k-means clustering. When tested on the PH2 and ISIC 2017 datasets, the suggested technique achieved an accuracy of 92% and 96%, respectively[14]. For the ISIC 2017 dataset, the Dice coefficient values are 0.82 and 0.92 for PH2.

The contour energy is calculated by adding the internal energy, which indicates the contour's flexibility and smoothness, and the external energy, which reflects the contour's energy directed toward the item in the image. This method approaches the contour energy as a minimal partition problem in order to minimize it. After applying level set formulation, it transforms into a "mean-curvature flow"-like developing active contour that vanishes at the desired boundary[15]. This approach, unlike earlier suggested active contour segmentation strategies, can be used to segment objects whose boundaries are not clearly delineated by gradients since it does not rely on the edge function or the image gradient to stop curve evolution.

IV.SYSTEM DESIGN

SYSTEM ARCHITECTURE

Below diagram depicts the whole system architecture.

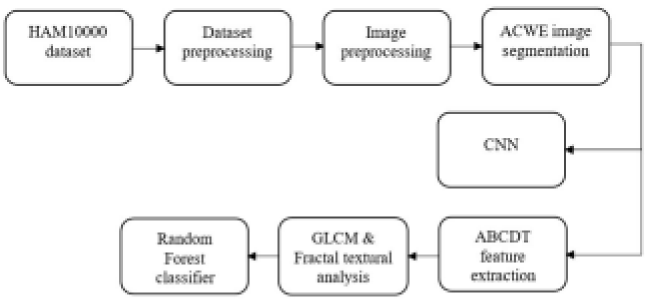

Fig 1. Methodology followed for proposed model

ISSN: 2348-1358

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V. SYSTEM IMPLEMENTATION

MODULES

Gathering and preparing the data:
The HAM10000 dataset, which contains 10015 skin lesion pictures representing seven different types of skin cancer, was used for this project.
Preprocessing the data: The HAM10000 dataset is uneven, with more pictures of one type of skin lesion (nv) than any others. Preprocessing techniques such as random oversampling and data augmentation are employed to correct the imbalance and increase the model's resilience.
Image Preparation: Filtering: Image denoising uses methods such as median filtering to minimize noise in the images.
Hair Removal: Morphological approaches like the blackhat transform are used to remove artifacts such as hair.
The preprocessing techniques are intended to increase the quality of the supplied image while also removing unwanted artifacts that could inhibit accurate diagnosis.
Using Active Contours Without Edges (ACWE) for image segmentation
To extract the region of interest (skin lesion) from the input image, image segmentation is employed.
The Active Contours Without Edges (ACWE) approach is used to segment levels based on Mumford-Shah segmentation.
The active contour model evolves to decrease contour energy while also determining the intended borders of the skin lesion.
Feature deletion: Features are retrieved from segmented skin lesion images to define their properties.
Asymmetry, irregular borders, color variation, diameter, and texture are all examples of characteristics.
Textural analysis techniques such as Fractal Dimension Texture Analysis (FDTA) and Gray Level Co-Occurrence Matrix (GLCM) are used to extract texture-related features from photographs.
Classification of Features:
Feature classification uses machine learning classifiers such as Random Forest and Convolutional Neural Networks (CNNs).
These classifiers use the collected features to distinguish between different types of skin cancer.
The performance of the trained classifiers is evaluated, and they are finally simulated to detect skin cancer in real time.

VI .RESULTS AND DISCUSSION

CNN Based Categorization Tensorflow's 'v2.10.0' library was utilized to build the CNN model. The CNN model is preceded by data augmentation layers such as resizing, rescaling, random rotation, random flip, and random zoom. This enables real-time image augmentation during training, as opposed to batchwise generation. The classification accuracy in the training phase was 90.72%, while in the validation phase it was 91.97%. After training, a real-time simulation is utilized to forecast random images of skin cancer. The simulation is conducted with OpenCV, and the images are displayed on, say, a smartphone.

The CNN model in the simulation achieved a 90% detection hit ratio, indicating that 9 out of 10 images were properly detected. Simulating real-time skin cancer diagnosis using CNN. Using Random Forest for classification The data from ABCD, GLCM, and FDTA is fitted to the Random Forest classifier with the RBF kernel approximation. An accuracy of 89.82% was obtained. In a real-time simulation, the Random Forest classifier achieved a 50% success rate despite its greater accuracy.

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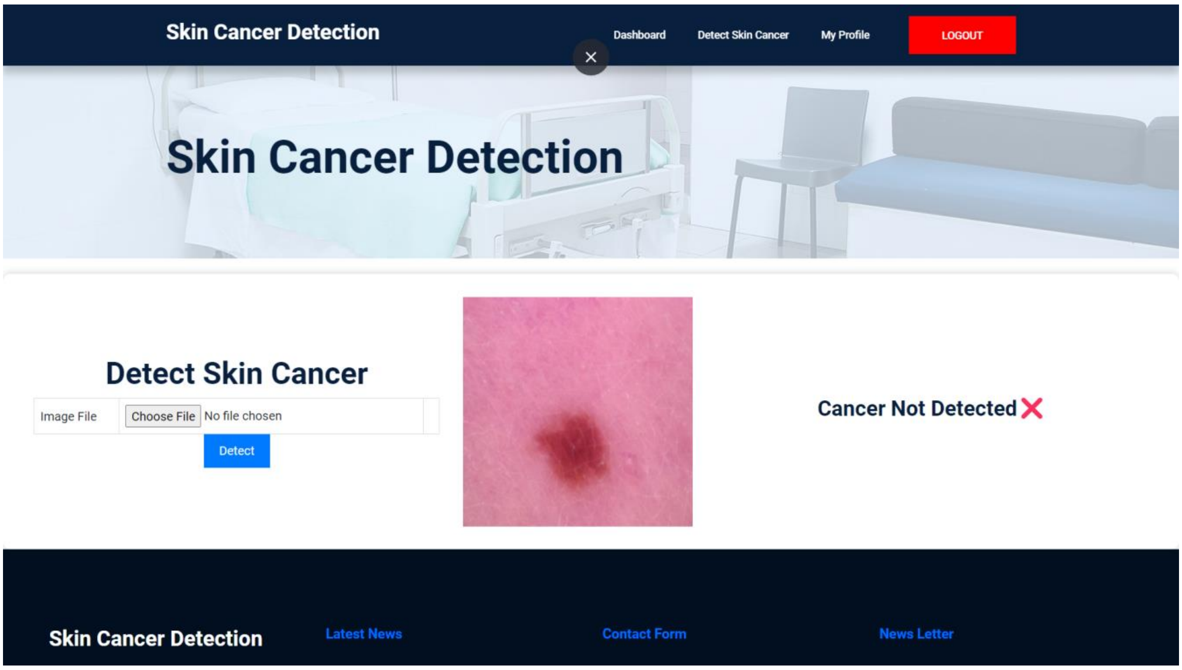

Fig 3.Uploading Skin decesice Image

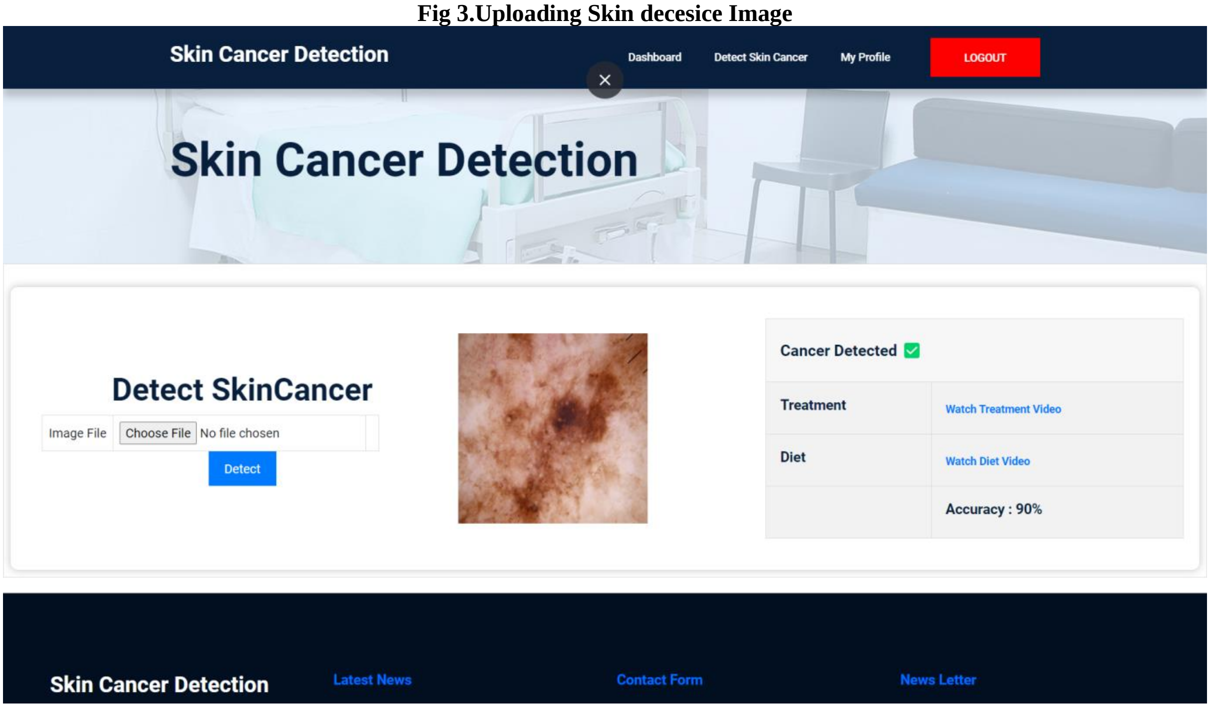

Fig 4.Predection of Skin cancer

VI I.CONCLUSION AD FUTURE WORK

ISSN: 2348-1358

Impact Factor: 6.901

NAAS Rating: 3.77

CNN and Random Forest classifiers are employed in this study to classify the HAM10000 dataset's seven skin lesion categories. CNN and Random Forest classifiers achieve accuracy rates of 91.97% and 89.82%, respectively. OpenCV is used to simulate classifiers in real time. The CNN model outperformed the Random Forest classifier in terms of correctly detecting the seven different types of skin cancer. The CNN model's detection latency is obviously high, limiting throughput. Active contour snakes combined with real-time object identification algorithms improve performance dramatically, making them perfect for real-time embedded systems. This device, which can be simply installed on a microcontroller interfaced with a high-resolution camera, allows doctors to quickly diagnose skin cancer.

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