The Use of Resnet50 for Skin Cancer Analysis

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Abstract:- Skin cancer remains a critical global health concern, with over 2.1 million cases diagnosed annually, many in areas with limited access to dermatological care. Providing an accurate diagnosis on time is essential but challenging in rural and backward areas. The growth of artificial intelligence (AI) and deep learning has shown significant potential in aiding skin cancer detection and classification. This study focuses on using deep learning models like CNN for categorization of skin lesions. This review discusses different CNN architectures and methodologies, emphasizing the need for further innovation to enhance model accuracy across multiple classes, thus supporting widespread, accessible diagnostic solutions.

Keywords:- *AI (Artificial Intelligence), CNN (Convolutional Neural Networks), API (Application Program Interface), HAM10000 (Human Against Machine With 10000 Images) , VGG16 (Visual Geometry Group).*

I. INTRODUCTION

Skin cancer classification has become a critical area of research on account of the rising incidence of cases globally. Conventional diagnostic techniques are reliant on dermatological expertise, which can be limited in availability, especially in outlying regions. CNN has emerged as an effective technique for image-based classifications and shows great promise in dermatology for analyzing skin lesions. CNNs can automatically learn and detect complex features within medical images, enabling efficient and accurate categorization of skin cancer types without manual feature extraction.

The goal of this project is to develop a CNN-based model that can distinguish between malignant and benign forms of skin cancer. By training the model on a diverse set of dermoscopic images, this project seeks to leverage CNN's capability to identify subtle distinctions between malignant and benign lesions, thus aiding in more accurate diagnoses. The outcome of this project could potentially support healthcare professionals in making faster and more reliable assessments, enhancing early detection efforts, and improving patient care outcomes indermatology.

II. LITERATURE SURVEY

[1]. The study uses refined deep learning models, specifically DenseNet-121, to analyze the classification of skin cancer. Data was sourced from HAM10000 and ISIC datasets, comprising 3297 RGB images labeled as cancerous or non- cancerous. Various machine learning (CNN, SVM, Random Forest) and adapted learning models (EfficientNetB0, ResNet34, VGG16, Inception version 3, and DenseNet121) were evaluated. DenseNet-121, with additional dense layers and a sigmoid activation function, yielded the highest accuracy at 87%. The study concludes that fine-tuned DenseNet-121 is highly suitable for grouping skin diseases into different categories, enhancing diagnostic precision, but recommends subsequent research with more diverse skin color data for better generalization.

[2]. This study utilized 2,357 images from the ISIC database, featuring nine skin cancer types, and applied pre-processing approaches. Deep neural model, specifically ResNet50, were employed for image partition, attribute extraction, and classification. By leveraging these methods, the model attained an accuracy of 91.32%, outperforming previous models. This research underscores the efficacy of CNNs in skin cancer detection, demonstrating the capability of automated diagnostic tools to enhance early cancer detection effectiveness and suggesting that future models could further refine accuracy by incorporating diverse datasets and improved feature extraction.

[3]. The study developed a pioneering deep CNN structure, SkinLesNet, aimed at differentiating skin tumor types and detecting melanoma. The researchers used the PAD-UFES- 20-Modified dataset, containing 1,314 smartphone images of three skin lesion types: melanoma, nevus, and seborrheic keratosis. The methodology included data preprocessing, augmentation, and training on Google Colab using TensorFlow and Keras. SkinLesNet's performance was evaluated and compared to established models like ResNet50 and VGG16, achieving a 96% accuracy, notably outperforming both. The study concluded that SkinLesNet could provide an accessible and effective tool for early melanoma detection.

[4].The paper presents a unique approach to skin cancer evaluation using a combination of feature-extracting neural network and discrete wavelet transformation (DWT) to enhance classification accuracy. The study employs the HAM10000 dataset, focusing on the preprocessing of skin disease images, DWT-based feature extraction, and CNN-driven classification to boost the early detection of cancerous and non-cancerous lesions. By identifying critical features in images using DWT and applying CNNs for classification,The suggested model outperformed traditional models like artificial neural architecture (ANN) in classification, with a sensitivity of 94% and specificity of 91%., significantly surpassing conventional models such as artificial neural architecture (ANN) and multilayer perceptrons with respect to accuracy. This method provides a robust framework for clinical application, demonstrating that CNNs combined with DWT can offer fast and accurate evaluations, supporting early diagnosis and better treatment outcomes. While the model's efficacy is promising, additional refinements are recommended for computational efficiency to better suit real-time clinical applications.

[5]. This study examined skin cancer grouping leveraging fusion of various models, combining DenseNet-201, MobileNet, and ResNet-50 with a support vector model. Usingthe World Symposium on Biomedical Imaging 2016 dataset, models were trained on augmented dermoscopy images of benign and melanoma lesions. The methodology incorporated transfer learning from pre-trained CNNs and applied an SVM classifier for enhanced classification. The hybrid model combines DenseNet-201 and MobileNet accomplishing the greatest precision of 88.02%. The results suggested that hybrid CNN-SVM models improve classification accuracy, suggesting future improvements with diverse datasets and parameter tuning.

[6]. This paper utilized CNN-based techniques to group skin cancer into various types , leveraging the ISIC dataset with 3,297 non-cancerous and cancerous lesions. Through an 80-20 split for instruction and assessment, and extensive hyperparameter tuning, the CNN achieved a 98.5% accuracy, significantly outperforming DNN models. The CNN's convolutional layers, which effectively extract essential features from targeted regions, allowed the model to reduce parameters and improve classification accuracy and speed. This study concludes that CNNs offer promising precisionand efficiency in in clinical imaging for skin cancer identification.

[7]. This paper presents a comprehensive review of recent advancements in analysis of diverse categories using deep learning. The review identifies common deep learning models and methodologies such as convolutional neural networks (CNNs), transfer learning, and ensemble methods. The authors evaluate these techniques across various datasets like HAM10000 and ISIC, highlighting issues related to dataset bias and the necessity for improved model generalization. The paper concludes that despite the advancements in architectures diagnostic accuracy significantly,further work is needed on model generalizability and hardware compatibility for real-time clinical application.

[8] The application of neural networks to image-based skin cancer diagnosis is examined in this paper.Harnessing the ISIC 2018 dataset with 11,527 images, the study applied CNN frameworks ,including ResNet50, Inception Version 3, and Inception ResNet, with image preprocessing via ESRGAN for quality enhancement. Each model was fine-tuned for optimal accuracy, and the InceptionV3 model attained top- most accuracy level of 85.7%. This research underscores the impression of hierarchical learning in accurate and automated skin cancer detection, though further improvement on larger datasets is recommended for real-world applicability.

[9]. This paper presents an improved network, named SkinTrans, for segregating skin cancer images. The method leverages Vision Transformers (ViT) with multi-scale and overlapping sliding windows, enhancing image feature extraction through multi-scale patch embedding. Contrastive learning is applied to achieve similar encoding for like data, maximizing inter-class differences. Testing on the HAM10000 dataset and a clinical dataset achieved 94.3% and 94.1% accuracy, respectively, demonstratingSkinTrans's effectiveness. Results suggest this model could aid dermatologists in accurate diagnosis, though an extended research on clinical experiments are necessary to validate its robustness.

[10].This study offers a methodical evaluation of convolutional neural network applications in the categorization of skin cancer., comparing the functionality of AI-based models with human experts. It delineates the capability of CNNs to classify skin cancers, including melanoma, with accuracy comparable to or better than dermatologists in controlled settings. The review assesses CNN effectiveness on dermoscopic, clinical, and histopathological images, noting that CNNs generally perform well in binary and multiclass tasks. However, the study requires additional research in real-world clinical settings and on diverse populations to enrich the generalizability and clinical relevance of CNN-based tools.
[11]. This paper uses a two-stage model using CNN and SVM was implemented to classify melanoma and squamous cell carcinoma. Leveraging the U-Net for lesion segmentation and CNNs such as ResNet-152 for classification, the model achieved up to 90% accuracy, highlighting the possibilities of transfer learning and deep learning in medical evaluation. Future work proposed includes expanding model training with unscaled images to improve detection across diverse skin conditions.

[12].This paper presents a methodology for identifying and labeling skin cancers using image analysis andlabelling algorithms. Details from the ISIC 2019 dataset were used, consisting of 800 dermoscopic images. Key tools include the Dull Razor method, Gaussian and Median filters for preprocessing, and k-means clustering for segmentation. Feature extraction employed the ABCD method and GLCM, whereas classification was performed using a Multi-class Support Vector Machine (MSVM), achieving 96.25%

accuracy. This approach demonstrates a robust pipeline for early identification of skin cancer, enhancing diagnostic precision.

III. OBJECTIVES

- The project aims to develop a mechanism thatefficiently detects skin cancer from images, leveraging deep learning techniques.
- Key goals include ease of use, global accessibility, and high accuracy with a low false positive rate.
- Machine learning advancements in image recognition and visual data processing to support reliable skin cancer detection.
- The scope covers ongoing research, algorithm development, and early diagnosis, which can greatly improvetreatment outcomes.
- AI-based image analysis aids dermatologists in making precise and early diagnosis of skin cancer.

IV. PROPOSED SYSTEM

Our approach focuses on leveraging CNN to effectively categorize skin cancer pictures that are first altered into an array with a 32x32 pixel resolution. The RGB color channels are separated and stored individually in a CSV file, a procedure that entails breaking down the image into its component elements for subsequent analysis. Images are preprocessed through resizing, normalization, and augmentation to enhance model robustness. At last, the outputs are classified into benign and malignant types of skin cancers.

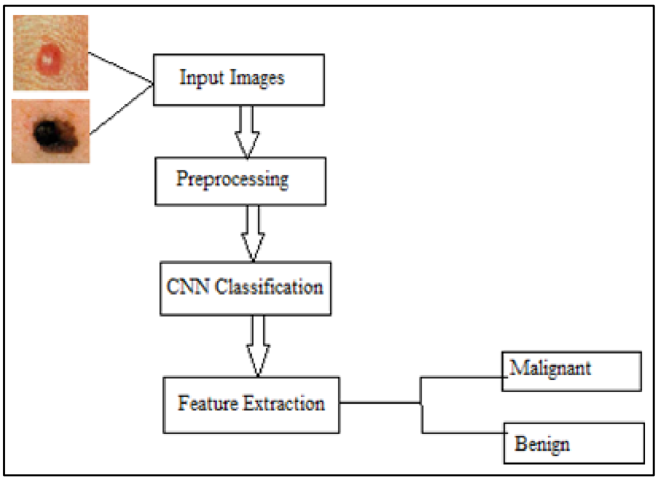

Fig 1 System Architecture

V. CONCLUSION

There have been major improvements in classification of skin cancer types using deep learning, especially with Convolutional Neural Networks, transfer learning models, andhybrid approaches. Studies consistently demonstrate that CNN-based models, such as DenseNet-121, ResNet, and specialized architectures like SkinLesNet, can attain high precision in binary and multiclass skin cancer division with some models surpassing traditional methods. Methods such as data amplification, preprocessing, and integration of SVM classifiers and discrete wavelet transformations have further improved diagnostic performance. However, challenges remain in model generalization across diverse datasets and real-world applicability, particularly in handling variations in skin tones and achieving reliable performance in clinical settings. This survey highlights the promise of deep learning for reliable and accessible skin cancer diagnostics, while also emphasizing the prominence of improving dataset diversity, model robustness, and clinical validation for broader implementation.

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