SKIN DEEP ADVANCED MODEL FOR ACCURATE SKIN DISEASE DIAGNOSIS

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Abstract. The mortality rate due to skin cancer is high, particularly in Western nations. Early detection of skin cancer cures the disease and prolongs human life. A common non-invasive technique for detecting skin cancer is a dermoscopy examination. Individual judgments by dermatologists determine the diagnosis, and the visual analysis of dermoscopy images requires additional inspection time. Current skin cancer classification algorithms rely solely on spatial information. However, they lack spectral domain data for lesion classification, leading to suboptimal model performance. This paper introduces novel hand-crafted features derived from cepstrum, spectrogram, and image-domain techniques to enhance skin cancer classification accuracy. These hand-crafted features incorporate both spectral and spatial information. Additionally, a newly developed 1-D multiheaded convolutional neural network (CNN) is trained using these features to classify skin lesions using the challenging HAM10000 and Dermnet datasets. The performance of the proposed network is compared with other state-ofthe-art approaches on the same datasets. According to experimental results, the proposed network achieved an accuracy of 88.57% on the Dermnet dataset and 89.71% on the HAM10000 dataset. Implementing this approach could improve the accuracy of clinical diagnosis.

Keywords: 1-D multiheaded convolutional neural network (CNN), skin disease, HAM10000, cepstrum, and dermoscopy pictures.

1. INTRODUCTION

Skin cancer is growing steadily all around the world due to unhealthy lifestyles and ignorance. It is creating serious issues for individuals in Western nations. There are going to be 12,500 skin cancer-related deaths and 104,000 new cases in the US in 2023, according to the American Cancer Society. Skin cancer kills two individuals every hour and diagnoses approximately 9,500 individuals every day in the United States alone.Excessive exposure to ultraviolet rays from the sun, allergies, infections, frequent use of tanning beds and solariums, advanced age, and a family history of the disease are the primary causes of skin cancer. The most common types of skin cancer include basal cell carcinoma, squamous cell carcinoma, actinic keratoses, and melanoma . Basal cell carcinoma is rarely fatal and occurs in the lowest layer of the epidermis. Squamouscell carcinoma, which develops in the outermost layer of the epidermis, can become fatal if

left untreated. The most dangerous type of skin cancer is melanoma, which can rapidly spread to other parts of the body and become life-threatening if not treated promptly .Melanoma originates in melanocytes, the cells responsible for producing melanin—the pigment that gives skin its color. In some cases, melanoma can develop inside the body, such as in the eyes, nose, or throat. While the exact cause of melanoma is not always known, exposure to ultraviolet (UV) radiation from sunlight, tanning beds, and tanning lamps significantly increases the risk.Reducing sun exposure may help lower the chances of developing melanoma. The risk of melanoma appears to be rising among individuals under 40, particularly women. Early detection plays a crucial role in ensuring effective treatment . Therefore, identifying melanoma in its early stages is vital for improving patient survival rates.Dermatologists still rely on dermoscopy images to screen for melanoma using conventional methods. Only a few broad screening techniques, such as the ABCD rule or the seven-point checklist, assist doctors in detecting skin cancer. These methods assess characteristics such as color, border, asymmetry, diameter, inflammation, evolution, and changes in sensation. However, distinguishing different types of skin cancer with the naked eye can be challenging due to the similarities in texture and pixel patterns among various skin lesions.One widely used non-invasive technique for diagnosing skin cancer is dermoscopy inspection. During this procedure, a gel is applied to the affected area, followed by the use of a magnifying instrument to enhance visibility. Compared to traditional examination methods, this imaging technique improves the accuracy of skin lesion diagnosis. However, dermoscopy image analysis requires clinical specialists, takes additional inspection time, and depends on the subjective judgment of dermatologists [8]. Therefore, an efficient, computerized process is essential for reliable skin lesion diagnosis.

2. LITRATURE SURVEY

[1].T. Swapna.et.al.,2021.The study explored CNN, ResNet, AlexNet, and InceptionV3 for skin disease classification. While CNN performed well on training data, it struggled with testing, whereas ResNet showed better accuracy overall. Improving dataset variance and size could enhance classification performance .[2].Adarsh Jadhav.et.al.,2023 The study developed a CNN-based model for skin disease classification, achieving 97.05% accuracy using the HAM-10000 dataset. This method enhances dermatological diagnostics by enabling faster and more precise disease detection. Future improvements could include expanding disease categories and integrating real-time monitoring systems.[3].Srushti.et.al.,2020.The system successfully detects dermatological diseases using image processing and deep learning. It is lightweight, cost-free, and user-friendly, making it accessible to a wide audience. Future improvements include expanding the dataset and increasing disease coverage for enhanced accuracy.[4].Sruthi Chintalapudi.et.al.,2021.The study developed a deep learning model for skin disease detection, achieving 91.74% training accuracy and 87.33% validation accuracy. It uses CNNs to classify skin conditions efficiently with minimal hardware requirements. Future improvements include expanding datasets and refining accuracy for early disease detection.[5]. Xia, Deneng.et.al.,2023.The study integrates deep neural networks and large language models for skin disease diagnosis, achieving a 93% validation accuracy. It combines image classification with interactive AI-based consultation to enhance diagnostic accuracy and user engagement. Future enhancements include refining reasoning capabilities and improving realworld applicability.

3. PROPOSED SYSTEM

The Skin Disease Classification using Artificial Intelligence Methods method aims to establish a systematic approach for developing and utilizing an efficient and accurate diagnostic system. Its primary goal is to leverage advanced deep learning models to enable early and precise detection of skin diseases, ultimately improving patient outcomes. This methodology consists of key steps, including data acquisition, preprocessing, model development, training, and evaluation.

3.1. Data Collection and Preprocessing

The dataset used for training includes a diverse set of images representing various skin conditions, sourced from publicly available databases and medical repositories. To enhance data quality and model generalization, preprocessing techniques such as image resizing, normalization, and data augmentation are applied.

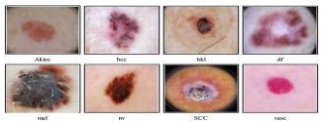

Figure 1

Figure 2

3.2. Model Development and Training

A Convolutional Neural Network (CNN) is implemented using TensorFlow for classification. The model architecture consists of essential layers, including Convolutional, Max Pooling, Flatten, Dropout, and Dense layers, which facilitate feature extraction and classification. The dataset is divided into training and test sets to ensure balanced learning. During training, model parameters are optimized using an appropriate loss function (categorical cross-entropy) and optimizer (Adam optimizer) to enhance performance.

3.3. Model Evaluation and Prediction

Once the model is trained, it is evaluated using key performance metrics such as accuracy, precision, recall, and F1-score to assess its effectiveness. The trained model is then tested on unseen images to classify skin diseases and non-skin disease conditions. The final classification results are analyzed, and areas for improvement are identified for further optimization. This structured methodology provides an efficient approach to developing an AI-driven diagnostic system for automated skin disease classification, supporting applications in telemedicine and dermatology.

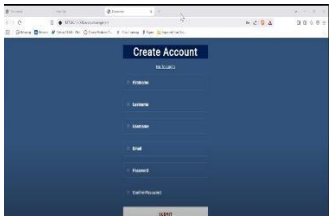

Figure 3

The user creates an account to access the service.

Figure 4

The user selects and uploads an image, likely related to a skin condition.

Figure 5

The uploaded image is processed, and the system detects Psoriasis disease based on the image analysis and helps to treat that disease

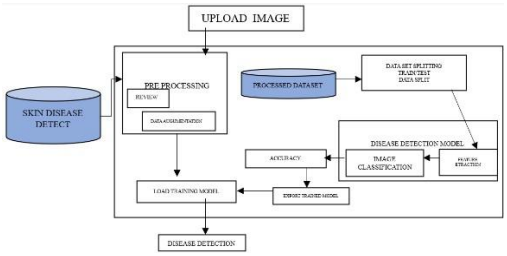

Figure 6 Architecure Diagram

6. MODULES

6.1. Importing Data & Preprocessing

The skin images are imported and preprocessed using Keras' image data generator.To ensure image quality and standardization, the following techniques are applied: Resizing, Rescaling, Zooming, Flipping.

6.2. CNN Model for Disease Detection

A CNN model is trained using structured inputs to enhance accuracy and precision.Dermatologists manually classify skin diseases based on:Asymmetry, Border features,Color patterns,AI models improve diagnostic accuracy and efficiency by automating this process.

6.3. LeNet-5 CNN Architecture with Modifications

The model incorporates convolutional, pooling, and encoder-decoder layers.It is optimized using:

Activation functions,Loss functions,Optimizers (e.g., Adam, SGD),Performance is evaluated using IoU (Intersection over Union) and the Dice coefficient.

6.4. Implementation with Django

The trained model is deployed using the Django framework.Users can upload images for real-time skin disease detection.

7. DATASET EXPLANATION

7.1. HAM10000 DATASET

The dataset consists of dermoscopic and clinical images, offering diverse representations of various skin lesion types. The HAM10000 dataset comprises 10,500 images of 224 × 224 pixels each. It has been divided into seven skin lesion categories:

Melanoma (mel): 1,113 images ,Melanocytic nevi (nv): 6,705 images ,Dermatofibroma (df): 115 images ,Benign keratosis (bkl): 1,099 images, Basal cell carcinoma (bcc): 514 images, Actinic keratoses (akiec): 327 images ,Vascular lesions (vasc): 142

7.2. SECOND DATASET WITH 19,500 IMAGES

This dataset consists of approximately 19,500 images of various resolutions, which were all converted to 128 × 128 pixels for consistency. Of the 23 classes present, seven were selected due to their variety and resolution differences:Eczema (ep): 1,235 images,Nail fungus (nf): 1,040 images,Basal cell carcinoma (akbcc): 1,149 images, Actinic keratoses,Vascular tumors (vt): 482 images,Melanoma skin cancer (msc): 463 images,Seborrheic keratoses (sk): 1,371 images,Urticaria hives (uh): 212 images

7.3. CEPSTRAL ANALYSIS

Cepstrum analysis involves a series of signal transformations to extract meaningful features. The computation of the cepstrum of a signal follows these steps:Fourier Transform (DFT): Converts the signal into the frequency domain,Logarithmic Function: Applies a log function to the magnitude spectrum,Inverse Fourier Transform (DFT^{-1}): Transforms the modified spectrum back to obtain the cepstrum domain representation.Mathematically, the cepstrum is expressed as:

$$DFT-1\{log|DFT\{f(x,y)\}|\}=C(x,y)$$

where | | denotes the magnitude operation.To simplify further processing, the 2D structure of C(x, y) is converted into a 1D form by concatenating its columns. This feature, represented as C(n), serves as a handcrafted feature in mixed-domain classification approaches. Cepstral analysis helps in capturing detailed textural and frequency-based characteristics, improving skin lesion classification.

7.4. SPECTROGRAM ANALYSIS

This technique is useful for detecting frequency variations in images and contributes to improved skin lesion classification.To compute the spectrogram of an image:Apply 2D Short-Time Fourier Transform (STFT),compute the squared absolute values of STFT coefficients,the spectrogram function for a signal f(n1,n2)f(n_1, n_2)f(n1,n2) is expressed as:

$$S(n1,n2,w)S(n\_1, n\_2, w)S(n1,n2,w)$$

where: mmm and www are quantized due to FFT-based DFT computation,w(n1,n2)w(n_1, n_2)w(n1,n2) serves as a window function.

8.RESULT AND DISCUSSION

The proposed one-dimensional (1-D) multiheaded convolutional neural network (CNN) is implemented in Python and run on a 3.20 GHz central processing unit with 256-gigabyte solid-state storage. Performance of the model is evaluated with different metrics including accuracy, F1 score, precision, specificity, sensitivity, and area under the curve (AUC).Two widely used datasets, HAM10000 and Dermnet, are employed for multiclass skin lesion classification. Data augmentation and class balancing strategies are applied for improving model performance. Both of the datasets have 4,375 dermoscopy images that are divided into training, testing, and validation subsets. That is, 80% of the images are kept for training, 12% for testing, and 8% for validation.The model takes hand-crafted features from spatial, spectral, and cepstrum spaces as input. Performance of the proposed method is assessed using the mean and the standard deviation of the evaluation metrics as well as the 95% confidence interval for statistical reliability.

9. CONCLUSION AND FUTURE WORK

Dermatologists are able to find that the automated classification of skin lesions helps them make decisions. In this paper, the authors have categorized skin lesions into different classes from the HAM10000 and Dermnet datasets. It is achieved by concatenating image, spectrogram, and cepstrum domain features to create new handcrafted features. The spectral and spatial information contained in the last concatenated features can be utilized to derive specific information from the problematic dermoscopy image files. The proposed 1-D multiheaded CNN is then used to classify skin lesions with concatenated features as input. Experimental results compared with other state-ofthe-art methods on the same dataset show that the proposed approaches have improved Acc, Spe, Pre, Sen, AUC, and F1 scores. Accuracy of the suggested method was 88.57% on the Dermnet dataset and 89.71% on the HAM10000 dataset. In the future, various biological signals (ECG, EMG, PCG, EEG, etc.) and images (CT, X-ray, MRI, etc.) will be utilized to verify the effectiveness of the suggested methodologies for other demanding datasets concerning skin lesions and other healthcare-based issues.

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