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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-of-the-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.

I. INTRODUCTION

Skin cancer is one of the most prevalent and fatal diseases in the world, with the highest mortality rate in the Western world. Early detection is crucial, with early treatment substantially improving the outcome and survival rate for the patient. Dermoscopy examination is one such common non-invasive technique for the diagnosis of skin cancer. Traditional diagnostic methods, however, rely heavily on the experience of the dermatologist, leading to inconsistency in interpretation and increased inspection time. Automated skin cancer classification systems have therefore been suggested to assist in the diagnosis to counter such issues.

Existing classification models predominantly depend on spatial information extracted from dermoscopy images. However, these models' absence of spectral domain information often hampers the performance. Spectral information can provide rich information regarding the texture, frequency components, and structure of skin lesions, which can be utilized to enhance classification performance.

This paper proposes a new technique that integrates spectral and spatial information to improve skin cancer classification. We propose hand-designed cepstrum, spectrogram, and image-domain-based features to obtain an overall representation of skin lesions. We also develop a 1-D multiheaded convolutional neural network (CNN) that is trained on the enriched features to perform skin lesion classification. We experiment with the proposed model on two benchmark datasets, HAM10000 and Dermnet, and it performs better than state-of-the-art techniques. Our method achieves an accuracy rate of 88.57% on the Dermnet database and 89.71% on the HAM10000 database, which makes it promising for clinical use.

Using spectral-domain information and implementing an innovative CNN architecture, our method can improve the reliability and accuracy of automatic skin cancer detection. The proposed framework can be employed as an effective assistant for dermatologists, with the potential for increased speed and accuracy in diagnosis, thus improving patient outcome

II. LITERATURE REVIEW

[1]This work improves skin cancer classification by using handcrafted features that mix spatial and spectral data. A novel 1-D multiheaded CNN trained on the HAM10000 and Dermnet datasets surpasses previous models, with 89.71% and 88.57% accuracy, respectively. The strategy may enhance clinical diagnosis.

[2]Skin conditions affect millions of people globally and can result in risks like skin cancer as well as psychological discomfort. Poor optical acuity in skin disease images makes diagnosis difficult in the absence of sophisticated equipment and medical specialists. In order to classify skin diseases, this paper suggests a deep learning method utilizing CNN architecture and three pre-trained models: AlexNet, ResNet, and InceptionV3. Images of burns and cuts, which are frequently misclassified by current approaches, were utilized in conjunction with a dataset that included seven disorders, such as melanoma, nevus, and seborrheic keratosis. By eliminating the need for manual feature extraction and data reconstruction, deep learning increases classification efficiency.

[3]Dermatology is complicated and challenging to diagnose, particularly in developing nations where therapy is costly. According to the WHO, skin conditions are the most prevalent non-communicable illnesses in India. Smartphones that use machine learning and image processing provide a cost-effective method of disease diagnosis. To identify skin conditions, the suggested system uses an application that analyzes and processes the photos with the help of artificial intelligence. Image processing is used to process the photos, and machine learning is used to produce the outcome.

[4]To identify different skin conditions, including sexually transmitted infections, this study investigates image categorization using deep learning. A trained algorithm examines the afflicted skin patches in photographs uploaded by users to a portal. Convolutional neural networks are used in the technique to identify diseases and extract features. All you need for a rapid and affordable diagnostic is a camera and a computer. The kind, severity, and spread of the disease are among the results.

[5Using the multimodal LLM VisualGLM in conjunction with image classification models on the HAM10000 dataset, this thesis investigates the application of large language models (LLMs) for the diagnosis of skin diseases (93% validation accuracy). Conventional AI techniques lack interaction but rely on deep networks such as ResNet and VGG. Our chat-based technology interacts with users, offers clarifications, and adds more information to improve diagnosis. This study shows the potential of LLMs in medicine, integrating AI-based image interpretation with human-in-the-loop interaction to improve diagnosis accuracy.

III. PROPOSED SYSTEM

The methodology for Skin Disease Classification using Artificial Intelligence Techniques is structured to ensure a systematic approach in the development and implementation of an efficient and accurate diagnostic system. The primary objective is to utilize state-of-the-art deep learning models to assist in the early and precise detection of skin diseases, thereby improving patient

outcomes. This methodology consists of several key stages, including data collection, preprocessing, model development, training, and evaluation.

A. Data Collection and Preprocessing

The dataset used for training the model consists of a diverse range of dermatological images representing various skin conditions. These images are gathered from publicly available sources and medical repositories. Preprocessing techniques such as image resizing, normalization, and augmentation are employed to enhance the quality of input data and improve model generalization.

B Model Creation and Instruction

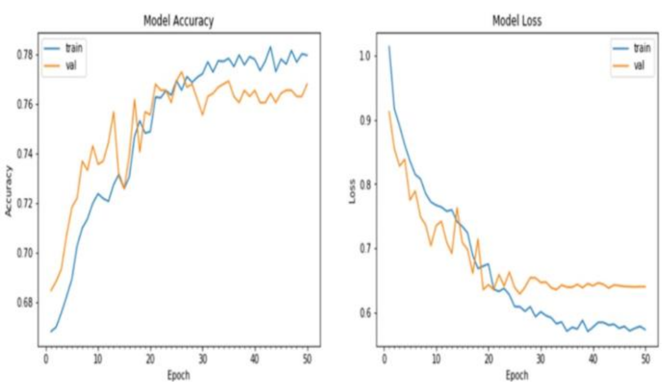
TensorFlow is used to implement a Convolutional Neural Network (CNN) for classification. The model architecture includes key layers such as Convolutional, max pooling, Flatten, Dropout, and Dense layers, which help in feature extraction and classification. The dataset is divided into training and testing sets, ensuring a balanced learning process. The training phase involves optimizing model parameters using an appropriate loss function and optimizer, such as categorical cross-entropy and Adam optimizer.

C. Model Evaluation and Prediction

Once trained, the CNN model is evaluated using accuracy, precision, recall, and F1-score to measure its effectiveness. The trained model is then tested on unseen images to classify skin disease and non-skin disease conditions. The final classification results are analyzed, and potential improvements are identified for further refinement.

This methodology ensures a structured and efficient approach to developing an AI-driven diagnostic system for automated skin disease classification, aiding in telemedicine and dermatological applications.

Graph 1



Graph 1 represents the Data Loss and Accuracy Vs Epoch

IV. MACHINE LEARNING MODELS

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AI and Deep Learning have transformed medical image analysis, providing automated and efficient diagnosis. The technologies are improving accuracy, decreasing workload, and enhancing patient care.

Data Science, an interdisciplinary science that brings programming, statistics, and domain expertise together, is crucial for AI innovation. AI mimics human intelligence, empowering machines to learn, reason, and forecast results. Deep Learning, a category of AI, employs neural networks to process enormous datasets with time-improving capabilities. CNNs, commonly applied to medical imaging, distinguish between malignant and benign skin lesions with high accuracy.

Artificial intelligence -based dermatology devices help physicians reduce errors and speed diagnosis. Future developments will address enhancing model interpretability, resolving ethical issues, and bringing AI into practice. Pivoting around overcoming such challenges as data privacy, algorithmic bias, and regulatory clearance will be key to safe AI adoption. By enhancing these technologies, AI can greatly improve skin cancer detection and therapy.

Table 1

Aspect	Merits	Demerits
Accuracy & Precision	CNNs trained on diverse datasets ensure accurate classification. TensorFlow optimizes model performance.	High computational power is needed for complex feature extraction.
Usability	The django-based interface allows easy image uploads, improving accessibility.	Requires specialized knowledge for model fine-tuning.
Processing Efficiency	Pre-processing techniques standardize images, improving input quality and reliability.	The model may struggle with unseen data, affecting generalization.
Continuous Learning	User feedback and updates enhance diagnostic accuracy over time.	Requires significant computational resources, making it impractical for low-power environments.

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Table 1 Describes the Merits and Demerits

V. MODULE DESCRIPTION

The module begins with importing and preprocessing skin image datasets using Keras' image data generator. Techniques like resizing, rescaling, zooming, and flipping enhance image quality and standardization. To provide an organized method for CNN-based classification, the dataset is separated into training, testing, and validation sets. Verifying dataset balance, especially between normal and afflicted skin photos, requires data analysis. These structured inputs are then used to train the CNN model, increasing illness detection precision and accuracy.

Manual classification relies on dermatologists analyzing skin lesions based on asymmetry, border irregularity, and color variations. While dermoscopy aids in manual diagnosis, AI-driven models enhance accuracy and efficiency. The LeNet-5 CNN architecture is adapted for skin disease classification, involving convolutional, pooling, and encoder-decoder layers. Activation functions, loss functions, and optimization algorithms like Adam or SGD fine-tune the model's performance. The trained model is evaluated using metrics like IoU and Dice coefficient to ensure reliability.

Finally, the trained model is deployed using the Django framework, allowing users to upload images for real-time disease detection. Django provides a secure, efficient, and user-friendly web interface, enhancing accessibility for medical diagnosis.

VI. PREPROCESSING OF THE DATASET

1) HAM10000 Dataset: The dataset [46] contains 10500 images altogether, each with a size of 224 by 224 pixels, and is divided into seven classes. Melanoma (nv), melanocytic nevi (mel), dermatofibroma (df), benign keratosis (bkl), basal cell carcinoma (bcc), actinic keratoses (akiec), and vascular (vasc) are the seven classes. Out of the total count of photos, there are 6705 of class nv, 327 of class akiec class, 514 in the bcc class, 1099 in the bkl class, 1113 in the mel class, 142 in the vasc class, and 115 in the df class.T here are numerous different types of photographs in the dataset, including dermoscopic and clinical images. Samples for each dataset class are presented in Fig. 1.2) Approximately 19,500 images of a large variety of pixel sizes comprise this dataset. This paper selects seven of the 23 classes because they are very variable and contain varying resolutions. Eczima images (ep), nail fungus (nf), basal cell carcinoma (akbcc), actinic keratoses, vascular tumors (vt), melanoma skin cancer (msc), seborrheic keratoses (sk), and urticaria hives (uh) are the seven categories that have been defined. There are 1235 photos in the ep class, 1040 in the nf class, and 1149 in the akbcc class.

Fig. 1

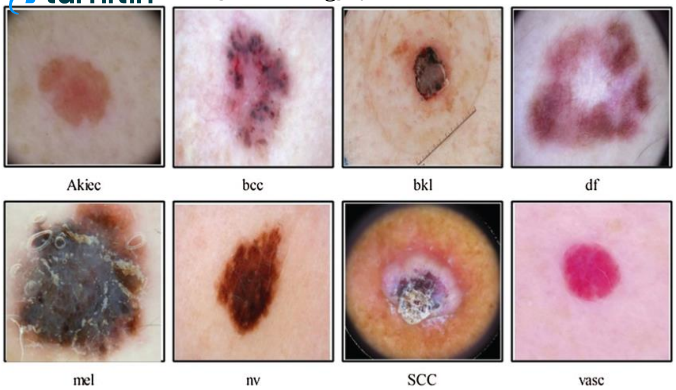


Fig. 1 illustrates the HAM10000 dataset's class-wise skin lesions.

Fig. 2

Fig. 2: Images of the Dermnet dataset's class-wise skin lesions

There are 482 images in the vt class, 463 in the msc class, 1371 in the sk class, and 212 in the uh class. All of the images are JPEG and have three RGB channels. However, these images are not of particularly good quality overall. All images are resized to 128 × 128 pixels to maintain consistency in image sizes. Each class's samples are illustrated in Fig. 2.

B.CEPSTRUM:

A chain of processes is utilized to achieve a signal's cepstrum. Initially, a Fourier transform is used to transform a provided signal into a frequency domain. The resultant term must then be subjected to a logarithmic operation. The result is then passed through an inverse Fourier transform. After an inverse Fourier transform, the ultimate signal that is produced is in the cepstrum domain. Any signal f (x, y) has the cepstrum c(x, y) as follows [12]:

$$DFT-1\{\log|DFT\{ f(x, y)\}|\} = C(x, y)2 \quad (1),$$

where the magnitude operation is denoted by ||. Concatenating the columns of C(x, y) to create a single column that transforms the 2-D form of C(x, y) into 1-D. C(n), which is one of the components of the proposed new mixed domain hand-crafted features. A picture's cepstrum gives more specific information regarding that image. This compressed data may be trustworthy for classifying the different types of skin lesions.

C.SPECTROGRAM:

In the analysis of 1-D signals, such as speech and biological signals, spectrograms are commonly employed. However, spectrograms are now employed in a relatively limited variety of computer vision applications[13]. A spectrogram is a visual and qualitative representation of the frequency range of a signal as it changes with time. An image undergoes a 2-D STFT to obtain its spectrogram. The absolute values of the STFT coefficients are squared. The STFT may be utilized to compute the spectrogram of any signal f (n1,n2). Any signal f (n1,n2) possesses the following spectrogram S(n1,n2,w) [18]: where m and w are discrete and quantized due to the fast Fourier transform technique being utilized to generate DFT, and w(n1,n2) is a window function. With the combination of the two planes through maximum magnitude selection, S(n,w), a 2-D shape, is formed from S(n1,n2,w), a 3-D object. Concatenating the columns of S(n,w) into a vector S(n) gives
the 1-D version of the same.

VII. FEATURE EXTRACTION

1-D multiheaded CNN was utilized employing Python on 3.20 GHz CPU having 256 GB SSD to discriminate multiclass skin lesions based on the HAM10000 and DermNet databases. 4,375 images per database were utilized, splitting them into 80% training, 12% testing, and 8% validation. Data augmentation mechanisms like rotation, zoom, cropping, and flip were utilized for balancing training examples and enhancing generalization.

The model learns spatial (image), spectrogram, and cepstrum features, and the best performance is obtained with the concatenation of all three types of features. In comparison, spatial features alone gave the worst performance. The model was trained with the Adam optimizer for 30 epochs, batch size 32, and dropout rate 0.25 to avoid overfitting. Performance was measured in terms of accuracy (Acc), F1-score, precision (Pre), specificity (Spe), sensitivity (Sen), and AUC.

Evaluation yielded that data augmentation enhanced classification performance by 3-4% and AUC by 2-3%. The mean absolute error (MAE) in DermNet and HAM10000 was 0.1257 and 0.1142, respectively, indicating a high level of classification performance. Model training time was 1.42 hours, with an average prediction time of 1.29 seconds.

A confusion matrix evaluation identified that the model effectively classified akiec, bkl, df, and mel lesions, while NV lesions presented the highest misclassification rate. Feature concatenation strongly minimized false negatives and false positives, enhancing diagnostic accuracy.

Comparative assessments in Table 1 showes that the integration of spatial, spectrogram, and cepstrum features immensely surpassed the utilization of spatial features only. The robustness of the model was validated through low standard deviations in performance metrics, indicating stability.

In summary, the suggested 1-D multiheaded CNN successfully distinguishes between skin lesions, where feature concatenation enhances diagnostic quality and stability. The efficiency of the model, supplemented by data augmentation and fine-tuned feature extraction, is a good sign for its implementation as an automatic skin cancer diagnosis tool. In future research, further enhancing generalization and diminishing misclassification, especially for the difficult lesion class NV, would be worthwhile

Table 2

Parameters	Without data augmentation	With data augmentation
Acc (%)	86.28±0.36	**89.71 ± 0.24**
Sen (%)	86.06±0.32	**89.24 ± 0.20**
Pre (%)	85.94±0.20	**89.00 ± 0.24**
Spe (%)	89.42±0.40	**92.68 ± 0.20**
F1 Score	0.8600±0.04	**0.8912 ± 0.02**
AUC	0.9128±0.03	**0.9340 0.03**

Table 2 Analysis of the network on the test set for the HAM10000 dataset

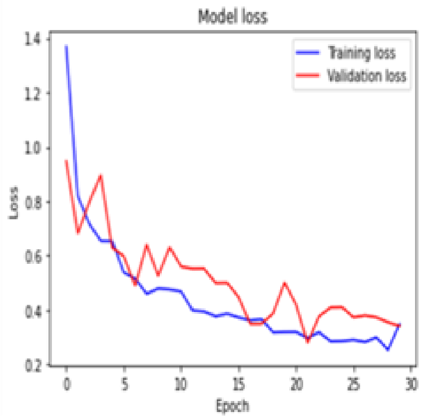
VIII. RESULTS AND DISCUSSION

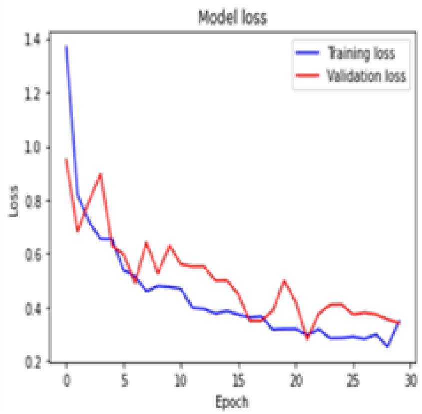
The suggested network is executed on the Python platform on the computer with the CPU at 3.20 GHz, 256 GB SSD. Accuracy (Acc), F1 score, precision (Pre), specificity (Spe), sensitivity (Sen), and the area under the curve (AUC) score are the performance metrics used to contrast the performance of the suggested 1-D multiheaded CNN. The performance parameters are calculated mathematically in the following way.

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + TN + FN)}$$

HAM10000 and Dermnet databases are used to classify multiclass skin lesions in the following way. Data augmentation is first used to augment the small sample of photographs for every class. Second, the training sample photos for every class in the datasets are balanced. 4375 dermoscopy images for every dataset are used for experimental investigation. Eight percent of all the images are used for the training set, twelve percent for the test set, and eight percent for the validation set. Second, the utilization of the spatial-, frequency-, and cepstrum-domain features is used to produce new hand-crafted features. Spatial (image), spectral (spectrogram and cepstrum), and concatenation of different groups of the spatial and spectral features (image and cepstrum, image and spectrogram, and image, cepstrum, and spectrogram) have been used as the inputs to the proposed network with both datasets to test the performance of the network. Based on the mean and standard deviation at the 95% confidence interval, the performance of the proposed network is evaluated [16]. The proposed methods section deals with the details of the generation of the handcrafted elements

GRAPH 2





Graph 2 Data loss of each model vs Epoch

IX. CONCLUSION

Dermatologists can discover that the automated classification of skin lesions assists them in making decisions. In this work, the authors have classified skin lesions into various classes using the HAM10000 and Dermnet datasets. This is done by concatenating image, spectrogram, and cepstrum domain features to develop new hand-crafted features. The spatial and spectral data present in the final concatenated features can be used to extract detailed information from the challenging dermoscopy image files. The suggested 1-D multiheaded CNN is then utilized to classify skin lesions by taking concatenated features as the input. Compared with other state-of-the-art methods on the same dataset, experimental results indicate that the proposed methods have better Acc, Spe, Pre, Sen, AUC, and F1 scores. The accuracy of the proposed method was 88.57% on the Dermnet dataset and 89.71% on the HAM10000 dataset. In the future, different biological signals (ECG , EMG, PCG, EEG, etc.) and images (CT, X-ray, MRI, etc.) will be employed to confirm the efficiency of the proposed methodologies for further challenging datasets related to skin lesions and other healthcare-related problems.

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