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AI-Based Hybrid Model for Detection of Multiple Skin Diseases Using Dermoscopy Images

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Abstract
Skin diseases are among the most common health conditions, and their early and accurate diagnosis is essential for effective treatment and improved patient outcomes. Conventional diagnosis of dermatological conditions primarily relies on visual examination and the expertise of dermatologists, which can be time-consuming and subject to inter-observer variability. This study proposes an AI-based hybrid model for the detection and classification of multiple skin diseases using dermoscopy images. The proposed approach combines advanced image preprocessing techniques with deep learning and machine learning methods to extract meaningful visual features and improve classification performance. Dermoscopic images are processed to reduce noise, enhance lesion characteristics, and normalize image quality before being analyzed by the hybrid model. Deep convolutional neural networks are employed for automated feature extraction, while complementary machine learning techniques are integrated to improve the discrimination of visually similar skin conditions. The model is designed to classify multiple dermatological diseases and distinguish abnormal lesions from healthy skin. Performance is evaluated using standard metrics such as accuracy, precision, recall, F1-score, sensitivity, specificity, and area under the ROC curve. By reducing dependence on manual interpretation and providing rapid, consistent predictions, the proposed system has the potential to support dermatologists in early screening and clinical decision-making. The study demonstrates the potential of hybrid artificial intelligence techniques as an efficient and scalable computer-aided diagnostic solution for multi-class skin disease detection from dermoscopy images.

Keyword: Artificial Intelligence, Deep Learning, Dermoscopy, Skin Disease Detection, CNN, Vision Transformer, Hybrid Model, ISIC, Image Classification, Medical Image Analysis

Introduction

Skin diseases represent a major healthcare challenge because many disorders exhibit visually similar characteristics while requiring different treatments. Early and accurate identification of suspicious skin lesions is particularly important in the detection of malignant conditions. Dermatologists commonly use dermoscopy to examine structures and patterns that are difficult to observe using conventional visual inspection.

The sun's UV rays are the main cause of skin tone, and there are many hidden issues that can arise in the skin that are not classified as skin illnesses. Even however skin illness is a common disease for which early diagnosis and classification are crucial for patient success and recovery, dermatologists execute the majority of noninvasive screening tests merely with the naked eye. This could lead to needless diagnostic errors brought on by human error because the disease could be easily overlooked. Furthermore, disease classification is difficult because many common skin diseases have very similar symptoms. Diagnostic processes must be accurate and prompt. Artificial intelligence research has lately been used to the diagnosis of skin diseases thru the use of machine learning algorithms and the vast amounts of data found in hospitals and healthcare facilities. Numerous previous works on the classification of skin diseases using machine learning were collected in this paper. Researchers employed a variety of systems, techniques, and algorithms in a series of preceding experiments. Numerous techniques have been used to classify skin diseases, with differing levels of diagnostic accuracy. In order to identify and predict the type of disease, many systems have relied on image processing and feature extraction techniques. Other methods have been developed to identify specific types of skin diseases using clinical characteristics and characteristics found by tissue analyses after a skin biopsy of the affected area. The main concepts of skin diseases are rashes, inflammation, and itching, or the skin being affected by unwanted body and facial creams. As a result, skin diseases can be treated with a variety of treatments, as well as skin creams and lotions tailored to specific skin types. While some skin illnesses may be inherited genetically, many skin problems are caused by environmental factors and inconsistent usage of skin care products. Migration frequently results in increasing skin pattern deterioration, which has a serious negative impact on the skin. Acne is the most prevalent of the four common skin diseases that affect people of all skin types. Atopic dermatitis is the second most common skin disease, and it primarily affects children and young adults. The three primary causes of skin tone damage are bacteria, viruses, and fungi, which have the most detrimental effects on the entire skin tone. The medical field uses a variety of equipment to detect and prevent various skin diseases, including eczema, which is now diagnosed in a variety of ways using ointments, lotions, and creams. This paper implements the hybrid based artificial in the neural approach. This section addresses the segmentation and classification approaches used by various researchers to improve the overall skin lesion categorisation in comparison to previous publications. However, the groups of images found in the given dataset are considered the various forms of collections. The various skin diseases images are classified as the basis which is in the lack of accuracy in the classification sections. The accuracy of the classification may be handled by the various forms of the collections, namely, using deep learning, artificial intelligence, and machine learning techniques. (i) Avoid focusing on arranging different image textures. (ii) In order to do this, the texture feature of the patterns—which has not been utilised in this work—must be considered along with colour and geometric elements. (iii) To improve performance, this segmentation-based classification model for skin lesions only used Inception v4; alternative deep learning models must be investigated. This research paper includes a literature review in Section 2, a suggested methodology in Section 3, a suggested approach in Section 4, a description of the dataset in Section 5, comparative results and analysis in Section 6, and conclusions and future work in Section 7.

Review of Literature

Deep learning has become an important approach in automated skin-lesion analysis. CNNs can learn image representations directly from training data without requiring manually designed features. Earlier approaches typically used architectures such as AlexNet, VGG, Inception, ResNet and DenseNet. More recent approaches have employed EfficientNet and transformer-based architectures.

The ISIC challenges have played an important role in establishing publicly accessible benchmarks for automated skin-lesion analysis. The ISIC 2019 challenge, for example, provided approximately 25,000 training images covering eight lesion categories and highlighted the difficulty created by severe class imbalance. Previous challenge solutions have used ensembles, different image resolutions, loss balancing, and metadata fusion.

Chen *et al*. used a closed-loop framework to implement skin disease recognition based on self-learning and extensive data collection. The skin disease classifications in the paper are based on artificial intelligence techniques, and the provided datasets are experimentally verified using LeNet-5, AlexNet, and VGG16. The multi-resolution-tract CNN with hybrid pretrained and skin-lesion trained layers was implemented by Kawahara *et al*. The multitrained skin classification using the multiple hybrid analysis of the skin texture classification yields better results than the current method. The digital diagnosis of hand, foot, and mouth diseases using hybrid deep neural networks, lightweight, and hybrid-based deep neural perceptrons was presented by Verma *et al*. The hybrid deep neural network is used to diagnose skin diseases, and MobileNet is used to classify the datasets. The automatic histologically-closer classification of skin lesions was implemented by Rebou^2 Filho *et al*. The feature extraction techniques were handled by SCM methods from the dataset collection, and the classifications technique was handled by the Fourier transform, which found its accuracy, sensitivity, average, mean correlation, etc. Finally, it explains the accuracy classifications of the images. Using artificial intelligence algorithms for skin disease classification with the ideal accuracy pattern, Alsaade *et al*. developed a recognition system for diagnosing melanoma skin lesions. The skin disorders are then further classified using different sorts of approaches. The survey on artificial intelligence for medical picture classification, the several survey types utilised in the classification of the accuracy method, and the early diagnosis and prevention of skin diseases were all implemented by Deepa and Devi According to Zhu *et al*. hybrid AI-assistive diagnostic models enable quick TBS diagnoses of cervical liquid-based thin-layer cell smears; these days, the precision of skin disease classification may be more important. The Computer-aided Diagnosis System (CAD) is used to identify skin illnesses, and Hameed *et al*. developed an intelligent computer-aided system for classifying multiple skin lesions. A deep convolutional neural network was used by Hemanth *et al*. to create the improved diabetic retinopathy detection and classification strategy, which is a new version of the diagnosis of the hybrid approaches in the classification of skin diseases. Khan *et al*. used deep learning features with enhanced moth flame optimisation to accomplish multiclass classifications and skin lesion segmentation. The mutual bootstrapping technique was used by Xie *et al*. to segment and classify skin lesions automatically. Typically, the accuracy of the segmentation and classification methods determines the categorisation of skin cancer, and the results are then validated using the dataset foundation. The unique hybrid deep learning strategy was adopted by Apar *et al*. 2 Computational Intelligence and Neuroscience 8483, 2022, 1. for skin lesion segmentation and classification; swarm intelligence and Region of Interest

(ROI) techniques are used to classify skin diseases. The Artificial Intelligent Based Approaches to Reflectance Confocal Microscopy Image Analysis in Dermatology were implemented by Malciu *et al*. Confocal-based diagnosis is essential for accurately classifying skin conditions. Skin cancer is currently regarded as the most dangerous illness, and Oliveira *et al*. developed computational techniques for the picture segmentation of pigmented skin lesions. In the Investigations on Brain Tumour classifications Using Hybrid Machine Learning Algorithms, Rinesh *et al*. utilised the multicoloured skin representation in the form of the disease classifications. The intelligent method for monitoring skin disorders was implemented by Połap *et al*. in this study. Melanomas are one type of skin disease. The Multiclass Skin Lesion Classification Using a Novel Lightweight Deep Learning Framework was implemented by Hoang *et al*. This study applies the novel method based on the classifications of skin lesions for Smart Healthcare. The Enhanced Deep learning technique for Brain Cancer MRI Image Classification Using Residual Networks was used by Ismael *et al*. to classify skin disorders, including meningiomas, gliomas, and pituitary tumours. This paper implemented the early collections of the datasets, while Garnavi *et al*. used hybrid thresholding on optimised colour channels to perform boundary identification in dermoscopy images. The accuracy of the image classifications in COVID-19 patients was proposed by Chieregatoet *et al*. using a hybrid machine learning/deep learning COVID-19 severity predicting model based on CT images and clinical data. 3.

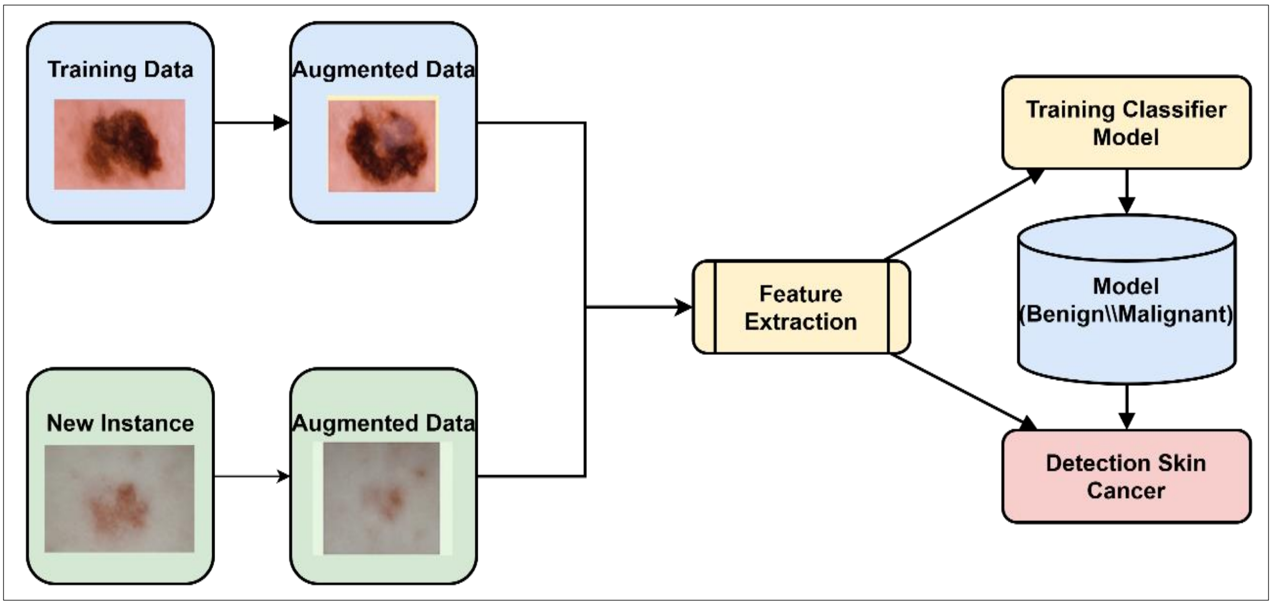

Fig 1: Architecture of deep learning in skin cancer detection

Proposed Methodology:

According to the overview of the proposed method, the fundamental ideas of the image processing technique should be expressed digitally; the majority of the disease classifications are simply involved in the form of different algorithm types. Figure 1 suggests that the image processing techniques are involved in the following ways in the overview of the proposed approach: the given input data sets undergo preprocessing techniques, which are handled by using the median filter in our proposed approach; the preprocessing techniques help to remove the noise in the images, and the median filter eliminates the salt and pepper noise in the given input images. Following the completion of the preprocessing procedure, the segmentation process was carried out by lowering the dimensionality space in the entire image, which helped to sharpen and smooth the edges throughout. The segmentation process is followed by the feature extraction process, which is regarded as the dimensional reduction process in the entire image processing. As a result, the individual images in the entire dataset are divided into more manageable groups; in our paper, the given collections for skin diseases are extracted using the Structural Co-Occurrence matrixes. This process is crucial to image processing because the higher quality of the dimensional quality reduction in the entire network system leads to more accurate results in the image classifications. For the categorisation of full-scale photos, our suggested method offers an improved Convolutional Neural Network. Lastly, our suggested article contrasts with the current methodology across the whole image processing system.

Proposed Approach

Our suggested method for classifying skin diseases is put into practice. The segmentation process is somewhat similar to the feature extraction process; the segmentation process manages the division or the region of the entire images in the entire network process; the feature extraction techniques in our proposed methods show that the more valuation results in the entire network, the structural Co-Occurrence is one of the major techniques that provide enhanced accuracy in the entire results in the image processing; the combination of the feature extraction When compared to the current methods, the classification in ECNN and SCM exhibits higher accuracy. The suggested method for classifying skin illnesses is shown in Figure 2, and our suggested strategy uses the median filter for the preprocessing technique—one of the most important methods in the image processing system.

Preprocessing: The preprocessing in the image processing helps to remove the noise in the entire image processing technique. the main function of the image processing technique is to reduce the noise in the image by adding many types of filters and then the RGB images are converted into the greyscale images, In our paper implements that the median filter for removing the noise in the image. ,e preprocessing for each image can be gathered by using the following five steps, namely, Image resizing, Transformation to the greyscale images, Noise Removal, segmentation masks, and contrast adjustment. The median filter's speciality is to remove the noise in the image by adding the salt and pepper to the entire image. ,e Gaussian and the median filter are considered as the opposite complex filter thus the median filter acts as the intermediate and non-linear filter in the image processing; it provides the normalisation in the given data sets. ,e Gaussian filer is considered the linear filter in the image processing system.

CNN-Based Methods

CNNs learn hierarchical representations through convolutional filters. Early layers generally learn simple features such as edges and color transitions, whereas deeper layers learn complex patterns and lesion structures.

ResNet introduced residual connections that allow very deep networks to be trained effectively. EfficientNet further demonstrated that network depth, width, and image resolution can be scaled systematically.

CNNs remain attractive for skin-lesion classification because they efficiently capture local structures. However, convolution primarily operates within local receptive fields, which can make global relationships more difficult to represent.

Transformer-Based Methods

Vision Transformers divide images into patches and apply self-attention to model relationships between patches. This enables the model to capture global contextual information.

For dermoscopy, global information can be important because the diagnosis of a lesion may depend on relationships among multiple regions rather than an isolated texture. Recent skin-lesion research has explored transformer-based and hybrid architectures for classification and segmentation.

Hybrid CNN-Transformer Models

Hybrid architectures attempt to combine the advantages of CNNs and transformers. CNNs can provide strong inductive biases for local visual patterns, while transformers can model global dependencies.

Recent research has proposed hybrid approaches for skin-lesion analysis, including architectures combining Vision Transformers with convolutional networks. This supports the motivation for investigating a hybrid approach for multi-class classification.

However, the performance of a model should not be judged only by overall accuracy. Skin-lesion datasets may be strongly imbalanced, meaning a model can achieve high overall accuracy while performing poorly on minority disease classes. Therefore, balanced accuracy, macro-averaged F1-score, sensitivity and specificity should also be considered.

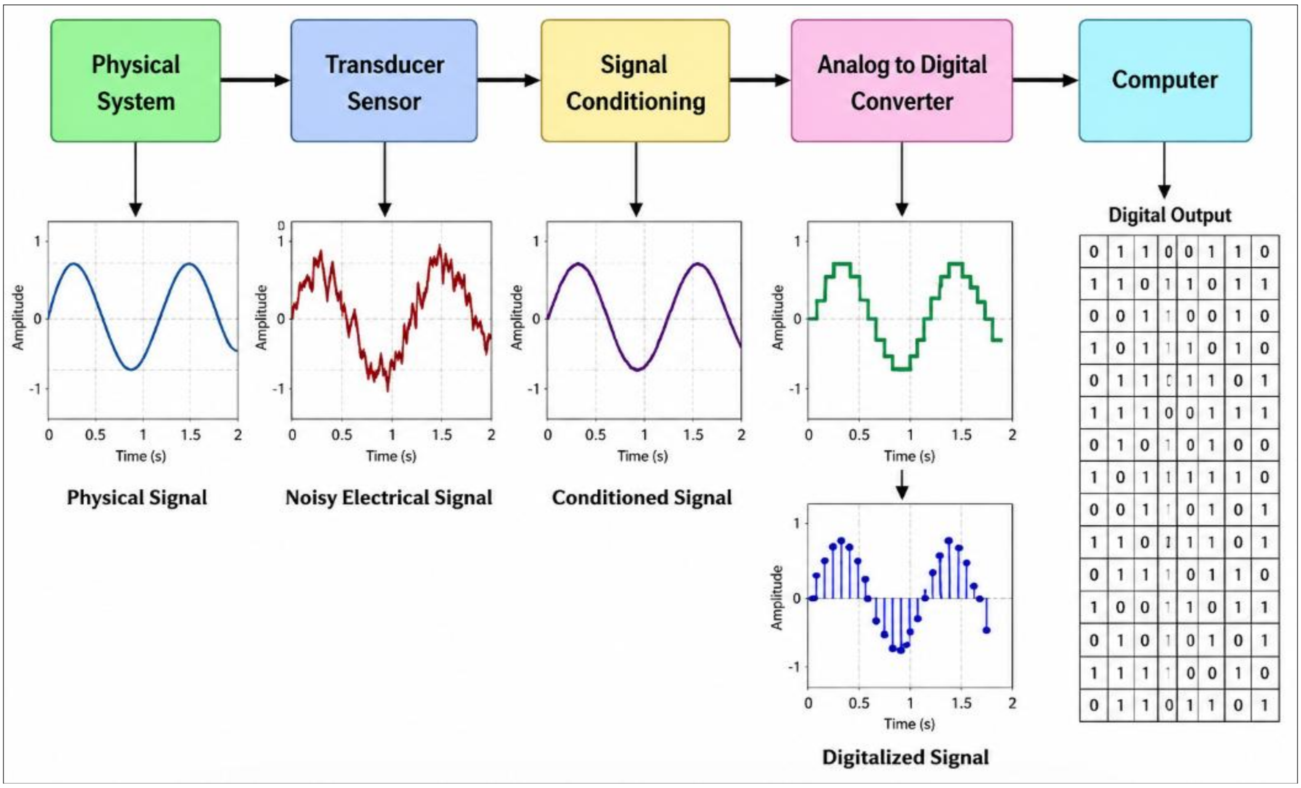

Fig 2: Digital Data Acquisition System

Dataset

ISIC Dermoscopy Dataset

The International Skin Imaging Collaboration (ISIC) Archive is selected as the primary data source for this research. ISIC provides a large repository of dermoscopic skin-lesion images associated with diagnostic and clinical metadata. The archive states that its images are collected from specialized clinical centers internationally and undergo privacy and quality screening.

For a reproducible multi-class experiment, the ISIC 2019 challenge dataset is a particularly suitable choice. The official ISIC challenge page lists 25,331 training dermoscopic images with diagnostic labels and an official test set of 8,238 images.

The Occurrence Matrix employs a comparable method; the SCM aids in discerning the composition of the complete image, hence enhancing the precision of feature extraction. Figure 3 illustrates the general Structural Co-Occurrence model utilised in image processing; the SCM employs both the original and filtered images, comparing the original images with the filtered counterparts [4]. Thus, the outcome of the SCM. The image processing yields enhanced precision in the domain of image processing. The ultimate outcome provides the data for the classification methods.

The ISIC 2019 dataset contains eight diagnostic categories:

- Melanoma (MEL)
- Melanocytic nevus (NV)
- Basal cell carcinoma (BCC)
- Actinic keratosis (AK)
- Benign keratosis (BKL)
- Dermatofibroma (DF)
- Vascular lesion (VASC)
- Squamous cell carcinoma (SCC)

The dataset is challenging because these categories are not equally represented. Consequently, class balancing must be incorporated into the training strategy.

Comparison Analysis and Results

Research indicates that melanoma ranks among the most prevalent skin disorders globally, with numerous researchers dedicated to its detection and prevention; however, the comprehensive data collection reveals shortcomings in the accuracy of classifications within the datasets. Our study contrasts existing methodologies, such as fast Fourier Transform with SCM feature extraction, support vector machine with SCM, CNN with SCM, and KNN with SCM, demonstrating that our enhanced output surpasses the overall results. Figure 5 presents the comparative outcomes for our suggested methodology.

Conclusion and Future Work

This study employs Structural Co-Occurrence matrices for feature extraction in the classification of skin diseases, utilising a Median filter for preprocessing, which effectively eliminates salt and pepper noise in image processing, thereby improving image quality; skin diseases are universally recognised as a significant risk factor. Numerous researchers are engaged in the early detection and prevention of diseases; consequently, we discovered that this novel methodology incorporates various existing techniques for classifying accuracy results across the entire network, and our approach yields a lower accuracy comparison. The simulation outcomes are based on parameters such as accuracy. Our suggested methodology achieves a classification accuracy of 97%, whereas other current models like FFT + SCM yield 80%, SVM + SCM provide 83%, KNN + SCM yield 85%, and SCM + CNN yield 82%. Future endeavours hinge on the enhanced precision of support vector machines in categorising dermatological conditions, while SCM is employed to oversee the feature extraction methodology.

Data Availability,

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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