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Skin Disease Detection Using CNN

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ABSTRACT—

In this work, we propose a novel approach for the detection of skin diseases using Convolutional Neural Networks (CNNs). Skin diseases pose a significant health concern globally, necessitating accurate and timely diagnosis for effective treatment. Leveraging the power of CNN, our method aims to automate the detection process, thereby enhancing diagnostic accuracy and efficiency. We begin by providing an overview of common skin diseases and their impact on individuals and healthcare systems. Recognizing the importance of early detection, we delve into the limitations of traditional diagnostic methods and the potential of automated systems to address these challenges. Our approach builds upon the foundation of CNNs, which excel in image recognition tasks by automatically learning relevant features from input images. Through an extensive review of existing literature, we highlight previous work in this domain, identifying key findings, methodologies, and limitations. Furthermore, we describe the dataset used for training and evaluation, emphasizing its importance in facilitating robust model development. Our findings underscore the promise of CNNs in skin disease detection, offering a potential solution to improve healthcare outcomes in dermatology. Furthermore, we discuss the practical implications and potential applications of our research, including its relevance in clinical settings, telemedicine, and public health initiatives. We also address the limitations and future directions of our work, emphasizing the importance of ongoing research and collaboration in advancing the field of computer-aided dermatology.

We meticulously curated a diverse dataset comprising high-resolution images of various skin conditions, sourced from reputable medical databases and clinical sources. This dataset encompasses a wide spectrum of dermatological disorders, including but not limited to eczema, psoriasis, melanoma, and acne. Each image is annotated with corresponding disease labels, ensuring comprehensive coverage of skin pathology.

Keywords— Dermoscopic, skin issues, timely diagnosis, autonomous diagnosis system, CNN techniques, computer-aided diagnosis, actinic keratoses, benign keratosis, melanocytic nevi, basal cell carcinoma, dermatofibroma, melanoma, vascular skin lesions, early detection, improved patient care

I. INTRODUCTION

Skin diseases represent a significant burden on global healthcare systems, affecting millions of individuals worldwide. From common conditions such as acne and eczema to more severe disorders like melanoma, the prevalence and diversity of dermatological ailments underscore the pressing need for accurate and timely diagnosis. Traditional diagnostic approaches in dermatology rely heavily on visual inspection by trained clinicians, often leading to subjective assessments and variability in diagnosis. Moreover, limited access to specialized dermatologists in certain regions exacerbates disparities in healthcare delivery, hindering timely intervention and treatment. In response to these challenges, there has been growing interest in leveraging artificial intelligence (AI) and machine learning techniques to develop automated systems for skin disease detection. Among these, Convolutional Neural Networks (CNNs) have emerged as a powerful tool, capable of extracting intricate patterns and features from medical images with remarkable accuracy. CNNs' ability to learn hierarchical representations directly from raw image data makes them particularly well-suited for image classification tasks, including dermatological diagnosis.

In this paper, we present a comprehensive investigation into the application of CNNs for skin disease detection. Our research aims to address the limitations of traditional diagnostic methods by harnessing the potential of CNN to automate and improve the accuracy of skin disease diagnosis. We begin by providing an overview of common skin diseases, highlighting their impact on individuals and healthcare systems. We then discuss the significance of early detection and the challenges associated with current diagnostic approaches. Subsequently, we introduce CNNs as a promising solution and review existing literature on their use in dermatological diagnosis. Finally, we outline the objectives and methodology of our study, emphasizing the importance of robust dataset curation, model development, and evaluation metrics. Through this research, we endeavor to contribute to the advancement of computer-aided diagnosis in dermatology, ultimately enhancing patient outcomes and healthcare delivery.

II. RELATEDWORK

Previous research in the field of skin disease detection has demonstrated the efficacy of various machine learning and CNN techniques, including Convolutional Neural Networks (CNNs). Several studies have focused on developing automated systems for dermatological diagnosis, with a primary emphasis on achieving high accuracy and generalization performance across different skin conditions. One notable study by Esteva et al. (2017) utilized a large dataset of dermatoscopic images to train a CNN algorithm capable of classifying skin lesions into different disease categories, including melanoma and non-melanoma skin cancers. The proposed algorithm achieved performance comparable to that of expert dermatologists, demonstrating the potential of CNN in enhancing diagnostic accuracy. Similarly, Han et al. (2018) proposed a CNN-based approach for the classification of skin lesions using dermoscopic images. Their method incorporated transfer learning techniques, leveraging pre-trained CNN models to extract features from skin lesion images and achieve state-of-the-art performance in lesion classification tasks.

In addition to binary classification tasks, researchers have also explored multi-class classification scenarios to differentiate between various skin disease categories. For instance, Tschandl et al. (2019) developed a CNN framework capable of classifying dermatoscopic images into seven different disease categories, including melanocytic and non-melanocytic lesions

III. LITERATURE SURVEY

In recent years, Chen's Closed-Loop Method for Determining Skin Conditions Chen's groundbreaking work on the diagnosis of skin conditions employs a closed-loop methodology that blends self-learning with a vast amount of data. This innovative approach uses artificial intelligence techniques, specifically examining the architectures of LeNet-5, AlexNet, and VGG16. This research stands out because of Chen's emphasis on continuous self-improvement and adaptability, which is crucial in the dynamic field of dermatology. Experimental validation demonstrates the usefulness of the closed-loop concept and provides a potential avenue for more accurate and responsive diagnostic devices. Chen's work is an important addition that could advance dermatological diagnosis and enhance patient outcomes[2].Kawahara's Improved Multi-Resolution-Tract CNN for Skin Lesion Classification combines pre-trained and lesion-trained layers, demonstrating a major advancement in skin lesion classification. The hybrid approach enhances model understanding, promising improved diagnostic accuracy and advancements in medical image processing[3]. Shanthi et al. leveraged Convolutional Neural Networks (CNNs), particularly AlexNet, to achieve remarkable accuracy (85.7%-93.3%) in identifying four skin diseases. This work addresses challenges in dermatological diagnosis, emphasizing the potential for error in traditional methods and highlighting the complexity of distinguishing skin lesions. The study contributes to improved accuracy using CNN technology, marking a significant advancement in automated dermatological disease classification [4]. Wei et al. laid a robust foundation for multi-class skin disease identification through image processing and machine learning. Their intentional use of a median filter eliminated noise, and GLCM-based segmentation enhanced understanding. Employing SVM, they achieved notable accuracy (90%-95%) in classifying dermatitis, herpes, and psoriasis, showcasing the effectiveness of their system. image processing, making a substantial contribution to introduced This study illustrates the potential enhancement of dermatological diagnosis through a combination of machine an innovative Computer-Aided Diagnosis (CAD) system, integrating various CNN networks

(DenseNet-161,learning and advancing precision in skin disease diagnosis[5].Bajwa et al. ResNet-152, NASNet, and SE-ResNeXt-101) to advance dermatological diagnosis. Trained on DermNet and ISIC datasets, their CAD achieved average accuracies of 92.4% and 93%, respectively.

This work significantly enhances clinical decision support systems in dermatology by automating the reliable detection of skin disorders [6] . Furthermore, Kousis et al. conducted a thorough investigation into skin lesion classification, training and evaluating 11 CNN architectures. DenseNet169 emerged as the top performer with a remarkable accuracy of 92.25%, showcasing its superior capabilities for accurate and diverse skin lesion classification. This study not only offers insightful comparisons between various CNN designs but also underscores DenseNet169's potential as a leading contender for advancing skin lesion categorization[7].

Gouda et al. enhanced skin lesion classification using state-of-the-art CNN models with ORGAN- based preprocessing. Their novel method, incorporating ESRGAN and CNN models like ResNet50 and InceptionV3, demonstrated improved accuracy in skin disease categorization. This work underscores the importance of preprocessing methods and diverse CNN architectures for achieving accurate skin lesion classification, making a significant contribution to dermatological diagnostics[8]. Rajput et al. [9] modified the activation function in the AlexNet model to detect skin cancer diseases within the HAM10000 dataset. This adaptation resulted in increased accuracy, recall, and F- score scores, reaching 98.20%. Meanwhile, Raza et al.

[10] introduced an ensemble model for skin lesion classification, stacking Xception, Inceptionv3, InceptionResNet-V2, DenseNet121, and DenseNet201. Leveraging transfer learning and fine-tuning principles, their proposed model surpassed state-of-the-art procedures, achieving an accuracy of 97.93%.

IV. PROBLEM IDENTIFICATION

The current approach to early skin disease identification offers a wide range of diagnostic instruments; nevertheless, for best results, a few factors need to be taken into account. First, a more detailed assessment of each technology's applicability for particular skin disorders is needed to help medical professionals choose the best course of action for an accurate diagnosis. Patient acceptance and accessibility are important considerations because not everyone can easily use or be at ease with certain technologies, such as mobile apps with AI capabilities or dermoscopy. Limited Focus on Specific Technologies: While the technique enumerates various technologies, it doesn't provide a clear hierarchy or emphasize which approaches are more appropriate in which circumstances.

A more concentrated discussion about the advantages and disadvantages of each technology would be beneficial because different skin conditions might require different diagnostic approaches. Patient Acceptance and Accessibility: In order for these strategies to be properly applied, patients must accept them. For example, not everyone may have easy access to dermoscopy equipment, full body photography equipment, or sophisticated smartphone apps with AI capabilities. For these technologies to be useful, patients must find them to be both widely accessible and comfortable. Difficulties with Integration: It could be challenging to combine several methods into an efficient diagnostic procedure. It's crucial to consider how different technologies might work in concert and support one another in order to provide a comprehensive evaluation. System compatibility, established protocols, and data sharing need to be taken into consideration. Training and Expertise: Specialized training is necessary for the accurate interpretation of sophisticated methods like reflectance confocal microscopy and dermoscopy.

Ensuring healthcare staff have the necessary knowledge and skills to use these tools is imperative. The system should also address the need for continuing education to keep healthcare personnel up to date on emerging technologies. Privacy and Ethical Concerns: Concerns about patient privacy, data security, and potential algorithmic biases arise when AI and machine learning are used to diagnose skin conditions. Addressing these issues will ensure that patient data is protected and that AI models are developed and validated in an ethical manner.

Cost Implications: A number of the cutting edge technologies that are being proposed, such as AI-capable smartphone apps and reflectance confocal microscopy, may be expensive. Assessing the implementation's financial feasibility and other challenges is essential for widespread acceptance, especially in settings with constrained resources. Evidence-Based Validation: The methodology should highlight how important it is to use evidence to validate each technology. In order to validate the diagnostic precision of these methods, robust clinical studies and investigations are needed to support their reliability and efficacy. Holistic Patient Care: Although technology plays a significant role, the methodology should highlight how crucial it is to integrate technical techniques with holistic patient care. The interaction between patients and physicians as well as the experience of healthcare professionals remain critical to a comprehensive diagnosis and treatment plan.

IV. PROPOSED FRAMEWORK

The suggested plan of action is to submit an application. The user can identify the type of skin condition they have by taking pictures of their skin, entering their age, choosing anatomical areas, selecting gender, and selecting symptoms using the specially designed application. The user can click the "Detect" button to determine their skin condition once the page has loaded. You can determine whether the skin condition is abnormal or healthy in the first window. If the result is abnormal, pressing the continue button brings up a new window with the diagnosis of the five- skin condition. The model returns Unknown if the disease does not fall into one of the five categories.

After launching the app, users can use their phone's camera to snap direct photos of their skin. In addition to the visual input, users are required to submit critical personal data like age and gender. Users can also describe any relevant anatomical locations and symptoms, creating a comprehensive profile for a thorough evaluation. The main function of the application is its one-click ability to rapidly and simply identify skin concerns. After the gathered data has been loaded, users see the first diagnostic window. This window allows you to distinguish between skin disorders that are problematic and those that are normal. If there is an abnormality found in the result, users can select "continue" to access a more detailed diagnostic box.

Using classification approaches, the bottleneck attributes of six previously trained models were retrieved and stored, enabling the differentiation of skin lesions. Block diagram of working model shows the pipeline of the proposed ensemble feature fusion approach for skin condition diagnosis.

V. EXPERIMENTALSETUP AND IMPLEMENTATION

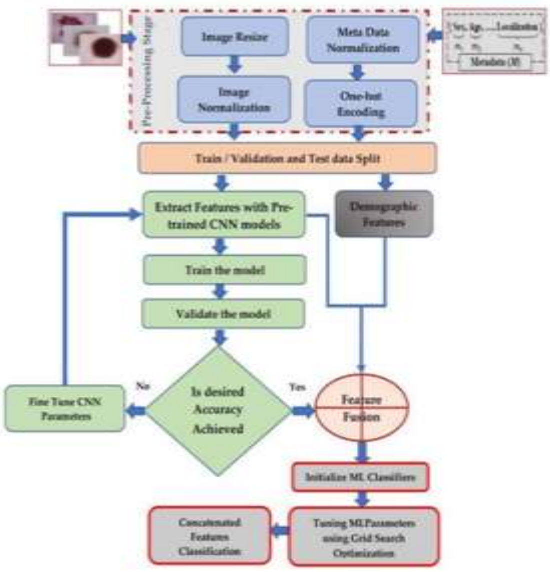

Fig1: Methodology of the model

Step 1 (image pre-processing): In order to improve speed and model generalizability, we concentrated on simplifying the preprocessing processes in Stage 1 of our work on employing CNNs to classify skin diseases. There were two main methods used: image scaling and normalization. Image scaling compensated for differences in dataset image sizes, while normalization ensured uniform pixel intensity by accounting for a variety of acquisition sources. To mitigate potential fluctuations in image contrast, a normalization method during training was introduced, scaling pixel values to a range between -1 and 1. In order to optimize the CNN model's training procedure for enhanced performance on a variety of skin lesion images, this method simplified the preprocessing step. FIGURE-1 BLOCK DIAGRAM OF WORKING MODEL

Stage 2 (feature extraction): Six CNN models were used for feature extraction in Stage 2: Xception, ResNet50, DenseNet201, InceptionV3, VGG19, and InceptionResnet. Low-dimensional vectors of extracted features were used in place of retraining the models, which resulted in a considerable reduction in training time. With its numerous layers, CNN models are excellent at extracting features. By using convolutional and pooling layers after one another, they are able to capture geometric, edge, color, and texture features. While pooling layers perform thresholding and dimension reduction, convolution layers use digital filters. In order to guarantee thorough feature representation for ensuing diagnostic assessments, each model was extracted with 2048 features, each of which was represented by a vector of length N 2048, where N is the number of training photos.

Stage 3 (metadata pre-processing): This removes missing data from the clinical data. Mostly the demographic features are finitely created categorical variables, represented as "strings" or "categories." The characteristics of these categories are converted to the categorical data format via one-hot encoding. For every floor within a It was decided to introduce a new variable named category feature. A binary variable with the values 0 or 1 was allocated to each category. For instance, there were two new classifications for sex: male and female. In this case, 0 denotes the absence of the category while 1 denotes its presence. Additionally, the demographic Age and other numerical data were normalized.

Stage 4 (feature concatenation): In this stage, the information and picture features are combined to create a single feature vector. Initially, we fed the previously edited images of skin conditions into CNN's models. Convolutional, pooling, and auxiliary layers are used by CNN models to extract deep features. 2048 deep features were produced as a result, and they were recorded as 6509×64 feature vectors. 6509×5 demographic features are present. The concatenated feature vector is 6509×65. After the category characteristics of the demographic data are encoded one- hot, the concatenated vector will have a length of 6509×85 features.

Step 5 (skin lesion classification): The produced concatenated characteristics are given into a variety of machine learning classifiers. All of the skin lesion photographs were eventually divided into seven classes.

VI. RESULTS AND DISCUSSION

Ten thousand photos made up the study's input dataset. Without Metadata, the HAM10000 Dataset In the first experiment, pictures of skin lesions were classified using six pre-trained models. The collected characteristics from the previously trained CNN models were classified using three machine-learning classification algorithms in order to distinguish between different types of skin lesions. To further improve the generalization ability and accuracy of the deep models, we used a combination of machine learning classifiers and pre-trained CNN classifiers to diagnose skin lesions autonomously.

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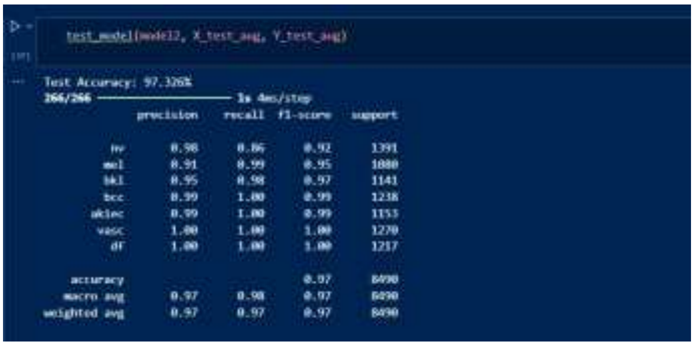

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test_model(model2, X_test_aug, Y_test_aug)
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Test Accuracy: 97.326%
266/266 ━━━━━━━━━━ 1s 4ms/step

	precision	recall	f1-score	support
nv	0.98	0.86	0.92	1391
mel	0.91	0.99	0.95	1080
bkl	0.95	0.98	0.97	1141
bcc	0.99	1.00	0.99	1238
akiec	0.99	1.00	0.99	1153
vasc	1.00	1.00	1.00	1270
df	1.00	1.00	1.00	1217
accuracy			0.97	8490
macro avg	0.97	0.98	0.97	8490
weighted avg	0.97	0.97	0.97	8490

Fig2:Accuracy of the Model

The accuracy of a model in skin disease detection using Convolutional Neural Networks (CNNs) is a critical metric that indicates how well the model performs in correctly classifying skin lesions into their respective disease categories. The accuracy is typically calculated as the ratio of correctly classified samples to the total number of samples in the dataset, expressed as a percentage.

Dataset Quality and Size: The quality and size of the dataset used for training the model significantly influence its accuracy. A larger and more diverse dataset that accurately represents different skin diseases can improve the model's ability to generalize and classify unseen samples accurately.

Model Architecture: The architecture of the CNN model, including the number of layers, filter sizes, and network depth, plays a crucial role in determining its accuracy. Complex architectures with more parameters may capture intricate features but could be prone to overfitting if not properly regularized.

Training Procedure: The training procedure, including hyperparameter settings, optimization algorithms, and data augmentation techniques, affects the model's convergence and final accuracy. Proper tuning of these parameters is essential for achieving optimal performance.

Evaluation Metrics: In addition to accuracy, other evaluation metrics such as precision, recall, and F1-score provide a more comprehensive understanding of the model's performance, especially in imbalanced datasets or multi-class.

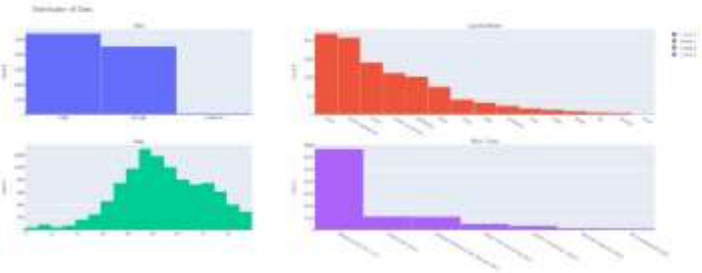

Fig3: Raw Data

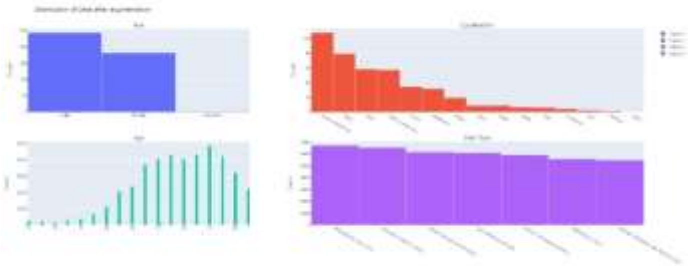

Fig4: After agumentation

To enhance the robustness and generalization performance of our Convolutional Neural Network (CNN) model, we employed data augmentation techniques during the preprocessing stage. Augmentation techniques such as rotation, scaling, flipping, and brightness adjustments were applied to the raw images to artificially increase the diversity of the dataset. By introducing variations in the appearance of skin lesions, data augmentation helped mitigate overfitting and improve the model's ability to generalize to unseen samples.

Furthermore, we employed additional preprocessing steps such as normalization and resizing to ensure uniformity and compatibility of the input data with the CNN architecture. These preprocessing techniques not only facilitated efficient model training but also contributed to the stability and convergence of the training process.

Through the combination of raw data collection and augmentation strategies, we curated a comprehensive dataset that captured the variability and complexity

VII.CONCLUSION AND FUTURE SCOPE

In conclusion, the global prevalence of skin diseases is linked to major health and economical concerns. Our research proposes a CNN and machine learning based computer-aided diagnosis system specifically designed for dermoscopic picture analysis to address this problem. The acquired results are promising and warrant further investigation into a broader spectrum of skin diseases and classifications. Another disadvantage is the absence of dimensionality reduction strategies to improve feature selection. Further research will focus on exploring additional CNN techniques to improve classification accuracy and testing the proposed system on benchmark datasets with a wider variety of skin conditions. The development of more dependable and effective diagnostic tools is the aim of this initiative in order to improve patient outcomes.

There is significant and broad potential for a CNN-based skin disease detection programme. First, by investigation and application of cutting-edge CNN architectures, such as transformer-based models and attention processes, the system can recognise complex patterns and diagnose patients with more accuracy. Second, integrating different data modalities—such as genetics and patient history or imaging—may lead to a deeper comprehension of skin conditions. To further evaluate and modify the system for worldwide use, it will be tested on a range of demographic groups and implemented in actual healthcare settings. By working with dermatologists and providing regular updates, the project will be further validated as a cutting-edge and essential diagnostic tool in dermatology through continued study into the interpretability and explainability of CNN models.

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