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SKIN DISEASE DETECTION

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ABSTRACT

Skin diseases are among the most common health issues worldwide, affecting individuals irrespective of age, gender, or geographical location. Early diagnosis plays a crucial role in preventing severe complications and ensuring timely treatment. This paper presents an intelligent skin disease detection system using advanced deep learning techniques for accurate classification of various dermatological conditions.

The proposed system is inspired by the base study, where multiple deep learning models such as Simple CNN, CNN with Dropout Layers, and CNN+LSTM were implemented. Among them, the CNN with Dropout Layers achieved the highest test accuracy of 88.6%.

To further enhance performance, this work proposes the implementation of advanced architectures such as DenseNet, ResNet, and Xception, aiming to achieve more than 90% classification accuracy. The system utilizes labeled image datasets, preprocessing techniques, and performance evaluation metrics including accuracy, precision, recall, and F1-score.

The results demonstrate improved classification capability, better generalization, and suitability for real-time applications in dermatological diagnosis.

KEYWORDS: Skin Disease Detection, Deep Learning, Convolutional Neural Network (CNN), DenseNet, ResNet, Xception, Medical Image Processing, Image Classification, Artificial Intelligence, Dermatology, Transfer Learning, Real-Time Diagnosis.

1. INTRODUCTION

Skin diseases represent a significant global health concern, affecting millions of individuals across all age groups and geographic regions. Common conditions such as acne, eczema, psoriasis, and skin cancer not only impact physical health but also influence psychological well-being and quality of life. Early and accurate diagnosis is essential for effective treatment and prevention of disease progression. However, traditional diagnostic methods rely heavily on clinical expertise, visual inspection, and sometimes laboratory tests, which can be time-consuming, costly, and dependent on the availability of trained dermatologists.

In recent years, advancements in Artificial Intelligence and Deep Learning have revolutionized the field of medical image analysis. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable performance in image classification tasks by automatically extracting complex features from raw image data. These models eliminate the need for manual feature engineering and enable highly accurate predictions, making them suitable for applications such as skin disease detection.

The increasing availability of large-scale annotated datasets and high-performance computing resources has further accelerated research in this domain. Automated skin disease detection systems can assist healthcare professionals by providing quick and reliable diagnostic support, especially in remote or underserved areas where access to dermatological expertise is limited. Such systems can also be integrated into mobile and web-based platforms, enabling real-time diagnosis and improving accessibility to healthcare services.

The base study that motivates this project proposed an intelligent system for real-time skin disease detection using CNN-based architectures. The study evaluated multiple models, including a simple CNN, CNN with dropout layers, and a hybrid CNN-LSTM model. Among these, the CNN with dropout layers achieved the best performance with a test accuracy of 88.6%, demonstrating the effectiveness of regularization techniques in improving generalization. However, the results also indicate that there is significant scope for improvement in achieving higher accuracy and robustness.

To address these limitations, the present work focuses on exploring advanced deep learning architectures such as Residual Networks (ResNet), Dense Convolutional Network (DenseNet), and Xception Architecture. These models are known for their superior feature extraction capabilities, efficient training mechanisms, and ability to handle complex image patterns. By leveraging transfer learning and optimized training strategies, the proposed system aims to achieve improved classification performance exceeding 90% accuracy.

2. LITERATURE SURVEY

Sl No	Paper No	Methods Used	Results	Limitations
1	Artificial Neural Network based Skin Disease Detection	Artificial Neural Network (ANN)	Around 80% accuracy achieved	Requires high processing power; lacks interpretability
2	Image Based Skin Disease Detection using Hybrid Neural Network coupled Bag-of-Features	Hybrid Neural Network, SIFT feature extraction, Bag-of-Features, K-means clustering, ANN trained using NSGA-II, PSO, and Cuckoo Search	Accuracy = 86.67%, Precision = 78.79%, Recall = 83.87%, F-measure = 81.25%	Limited to two diseases; computationally expensive feature extraction; small dataset; risk of overfitting
3	Robust Skin Diseases Detection and Classification Using Deep Neural Networks	Adaptive filtering + Region growing + CNN	96.768% accuracy achieved Limited dataset size	Limited dataset size
4	Skin Disease Analysis and Tracking based on Image Segmentation	Uses image segmentation techniques (K-means, FCM, IFCM, Otsu, Active Contour) with EAC and ROC evaluation	Active Contour gives best accuracy and enables precise wound measurement and tracking	Performance depends on image quality and noise and requires proper preprocessing
5	Skin Disease Analysis using Digital Image Processing	Improved Bag of Features (IBOF), SURF feature extraction, K-Means clustering, LIBSVM classification	Achieved high accuracy of 96%, confidence rate up to ~99.83%, low loss (0.03), high precision and recall (~99%)	Limited to only two diseases (Acne and Boil), dataset size relatively small, depends on image quality and controlled dataset
6	Determatological Disease Diagnosis Using Color-Skin ImagesColor	Color image processing, K-means clustering, Color gradient, Artificial Neural Network (ANN)	95.99% (stage 1), 94.016% (stage 2) accuracy	Limited to six disease types; high dependency on image color quality
7	Self-Paced Balance Learning for Clinical Skin Disease Recognition	A framework that combines "complexity of image category" (sample number + recognition difficulty) with the Self-Paced Learning (SPL) paradigm .	Outperformed state-of-the-art methods on SD-198 and SD-260 datasets .	Like other SPL algorithms, the model can be unstable at the beginning of the learning stage before more patterns are learned .
8	Genetic Algorithm Optimized Stacking Approach to Skin	Utilizes a stacked ensemble of multiple deep learning	Achieved a Top-5 accuracy of 74%, representing a 5%	Several individual architectures (like DenseNet121 and

	Disease Detection	architectures, including ResNet50, DenseNet121, and a Basic CNN .	improvement over existing works	MobileNet) showed
9	Federated Machine Learning for Detection of Skin Diseases and Enhancement of Internet of Medical Things (IoMT) Security	9-layer custom Convolutional Neural Network (CNN) featuring three convolution layers, max-pooling, and fully connected layers.	The proposed CNN outperformed benchmark models (AlexNet, VGG16) for acne, eczema, and psoriasis classes .	The model can only classify four types of skin diseases (acne, eczema, psoriasis, and rosacea)
10	Exploring Web Images to Enhance Skin Disease Analysis Under A Computer Vision Framework	Utilizes an instance-based transfer learning model to leverage external knowledge from "source domain" Web images to improve a "target domain" model .	The proposed method achieved an average accuracy of 88.80% on Dataset I and 85.14% on Dataset II	The current paper does not account for latent domains within Web sources
11	Self-Paced Balance Learning for Clinical Skin Disease Recognition	Self-Paced Balance Learning (SPBL): Introduces a "complexity of image category" metric combining sample number and recognition difficulty	Outperformed state-of-the-art methods on SD-198 and SD-260 datasets	The model can be unstable at the beginning of the learning stage, similar to other self-paced learning (SPL) algorithms.
12	A Skin Disease Detection System for Financially Unstable People in Developing Countries	People in Developing Countries • Image Preprocessing: Grayscale conversion and noise removal using Median filtering.	• Disease Coverage: Successfully detects 9 types of skin diseases (e.g., Eczema, Acne, Leprosy, Psoriasis).	Accuracy is highly dependent on the quality of the image and ambient lighting conditions when the photo is taken.
13	An Intelligent System for Real-time Skin Disease Detection and Medication	• Convolutional Neural Networks (CNN): A custom deep learning model used for real-time diagnosis of multiple skin condition	achieved the highest accuracy with 93.7% training, 81.1% validation, and 88.6% test accuracy	Mismatch: The hybrid CNN-LSTM approach performed
14	Skin Disease Detection using Machine Learning	Model Architecture: Utilizes a multiclass deep learning model based on Convolutional Neural Networks (CNN)	Achieved a test accuracy of 93.35%	Fine-grained Variability
15	Skin Disease Detection System	Convolutional Neural Network (CNN)	Improved accuracy on SD-198 and SD-260 datasets.	Initial model instability and sensitivity to lighting.
16	Skin Disease Detection	Convolutional Neural	Improved	High computational

	and Diagnosis Using Deep Neural Network	Network (CNN) and Deep Learning (DL) architectures.	diagnostic accuracy and early detection of skin conditions.	requirements and dependence on large, high-quality datasets.
17	Skin Disease Detection and Diagnosis Using Deep Neural Network	Use of ResNet50, ResNet18, and DenseNet121 architecture	The ResNet50 model achieved the highest accuracy of 88% using the DermNet dataset .	Dataset Quality: The DermNet dataset contained disorganized images
18	Artificial Neural Network based Skin Disease Detection	Deep Neural Networks (DNN), large dataset (129k images)	~91% accuracy, 87% sensitivity, 95% specificity	Requires large dataset and high computational resources

3. ATA DESCRIPTION

The dataset used in this project consists of labeled skin disease images collected from publicly available sources

such as Kaggle. According to the base paper �, the dataset is organized into two main

subsets: a training set and a

testing set. The training set is used to train the deep learning models by allowing them to learn patterns and features associated with different skin diseases, while the testing set is used to evaluate the performance of the trained models on unseen data. This separation ensures that the model's ability to generalize is properly assessed.

The dataset contains multiple categories of skin diseases, with each category stored in a separate folder. Each image is labeled according to its corresponding disease class, enabling supervised learning. The dataset includes various skin conditions such as acne, eczema, psoriasis, melanoma, ringworm, nail fungus, cellulitis, impetigo, and shingles. As illustrated in the sample dataset images shown in the base paper , the dataset covers a wide range of skin textures, colors, and disease patterns, which helps the model learn diverse features.

4. PROPOSED METHODOLOGY

The proposed system follows a structured workflow designed for high-precision real-time detection.

Input Dataset: The study utilizes a labeled dataset containing multiple skin disease categories, such as shingles, cellulitis, and impetigo, sourced from medical databases.

Preprocessing: Images are rescaled and normalized to a factor of (1/255) to ensure consistent input for the neural networks. Data augmentation—including rotation and flipping—is employed to enhance model generalization.

Deep Learning Models:

DenseNet: Utilizes dense blocks where each layer receives inputs from all preceding layers, promoting feature reuse.

ResNet: Employs residual learning to train extremely deep networks by mitigating the vanishing gradient problem.

Xception: Uses depthwise separable convolutions to improve computational efficiency and accuracy.

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Table I. Models used.

Model Name	**Key Technique**	**Description**
DenseNet	Dense Connections	Each layer is connected to every other layer to improve information flow
ResNet	Residual Connections	Uses skip connections to allow training of very deep neural networks
Xception	Depthwise Seperable Convolutions	Replaces standard convolution with depthwise separable convolution for efficienc

5. EVALUATION METRICS

To evaluate the performance of the model, several important metrics are considered to ensure both accuracy and efficiency. Training accuracy measures how well the model learns patterns from the training data, while test accuracy indicates the model's ability to generalize effectively to new and unseen data. Precision is used to measure the correctness of positive predictions, ensuring that the predicted disease cases are accurate, whereas recall evaluates the model's ability to detect all actual disease cases without missing them. The F1-score provides a balanced measure by combining both precision and recall, making it useful for overall performance evaluation. In addition, a confusion matrix is used to present class-wise prediction results and identify any misclassifications among different disease categories. Along with these accuracy-based metrics, training time is considered to assess the computational efficiency during the learning phase, and testing time measures how quickly the model can produce predictions for new input images. Together, these metrics provide a comprehensive evaluation of the model's performance.

6. CONCLUSION

This survey paper presents a comprehensive study of skin disease detection using deep learning techniques, highlighting the effectiveness of modern approaches in medical image analysis. The analysis of the base paper indicates that Convolutional Neural Network (CNN) models, particularly those incorporating dropout layers, deliver strong performance in classification tasks by reducing overfitting and improving generalization. However, there remains significant scope for further improvement in accuracy and robustness. To address these limitations, the proposed system focuses on implementing advanced deep learning architectures such as DenseNet, ResNet, and Xception, which are known for their superior feature extraction capabilities and efficient learning mechanisms. These models are expected to achieve higher accuracy, better generalization across diverse datasets, and improved computational efficiency. Overall, deep learning-based skin disease detection systems hold great potential to transform healthcare by enabling fast, accurate, and accessible diagnostic solutions, particularly benefiting underserved and remote regions where access to dermatological expertise is limited.

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