Resnet-50 Based Deep Learning Framework for Detection and Management of Lichen Planus and Psoriasis Using an Android Application

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Abstract:
Lichen Planus and Psoriasis are chronic inflammatory skin diseases that must be diagnosed and managed early to prevent a more severe level and guarantee better quality of life for the affected patients. Current diagnostic techniques for Lichen Planus and Psoriasis have been found to take a lot of time and greatly rely on the level of knowledge a dermatologist has. In an attempt to mitigate these risks, this paper proposes a ResNet- 50 based deep learning model for the creation of a user-friendly Android-based application for the management of Lichen Planus and Psoriasis. The proposed system uses the ResNet-50 deep learning model to classify the skin lesion images in the following classes: Lichen Planus, Psoriasis, and normal skin. This system also uses a transfer learning technique to optimize the performance of the model and simplify the complexity of the learning process. In the pre-processing of the image dataset, the following image processing techniques are used for better performance and robustness.For the practical application of the model, it is embedded into an Android-based application that enables the user to capture or upload images of the skin lesions using their devices. This provides the user with immediate prediction results, as well as important information on diseases, prevention, and basic management. The interface of the system is simple, intuitive, and user-friendly, making it accessible to both patients and HCPs. The framework allows for the early detection of diseases, reduces the need for manual screening, and monitors skin conditions in real-time. It also enables the application of efficient methods for the management of skin diseases based on the integration of deep learning techniques and mobile application technology. Thus, the specific role of the mobile health systems based on the ResNet-50 for the management and improvement of skin disease diagnosis has been presented in the specific article.
Index Terms: Lichen Planus, Psoriasis, Deep Learning, ResNet-50, Skin Disease Detection, Medical Image Analysis, An- droid Application, Mobile Health, Automated Diagnosis, Image Classification, Transfer Learning, Dermatology, Disease Management, User-Friendly System, Healthcare Technology

INTRODUCTION:

Skin-related disorders such as Lichen Planus and Psoriasis are chronic inflammatory conditions that significantly impact both the physical comfort and psychological well-being of affected individuals. These diseases often persist for long durations and may worsen if not identified and managed at an early stage. A major challenge associated with these conditions is that they frequently exhibit overlapping visual symptoms, including redness, scaling, and lesions, which makes accurate diagnosis difficult even for trained professionals. As a result, patients may experience delays in receiving proper treatment. This challenge becomes more severe in rural and resource- constrained regions, where access to experienced dermatologists is limited and primary healthcare providers may lack specialized expertise in identifying complex skin disorders. These limitations highlight the urgent need for intelligent, automated diagnostic support systems.

In recent years, artificial intelligence (AI) has emerged as powerful tools in the medical domain, particularly in the field of medical image analysis. Deep learning techniques have demonstrated strong capability in extracting meaningful patterns from complex image data, enabling reliable disease classification. Among various deep learning architectures, ResNet-50 has gained widespread recognition due to its residual learning mechanism, which allows very deep networks to be trained effectively without performance degradation. This architecture enhances feature learning by preserving essential information through shortcut connections, making it highly suitable for analyzing subtle variations in dermatological images.

The rapid growth of mobile technology and mobile health (mHealth) applications has transformed healthcare delivery. Smartphones have become widely accessible, even in remote areas, creating an opportunity to deploy intelligent healthcaresolutions directly to end users. Android-based applications, in particular, offer a cost-effective, portable, and user-friendly platform for integrating AI-driven diagnostic models. Embedding deep learning systems into mobile applications enables real-time disease analysis while reducing reliance on advanced medical infrastructure.

This work proposes a ResNet-50 based deep learning framework integrated into an Android application for the detection and management of Lichen Planus and Psoriasis. The application allows users to capture or upload skin images using a mobile device, after which the trained model analyzes the input and provides instant classification results. Beyond disease identification, the application also delivers essential disease-related information and basic management guidance to improve patient awareness and encourage early medical consultation.

The proposed system aims to assist healthcare professionals and patients by enabling timely preliminary diagnosis, reducing diagnostic delays, and improving access to dermatological support. By combining deep learning intelligence with mobile technology, the solution promotes accessible, efficient, and patient-centered skin disease management.The proposed approach aims to reduce dependency on manual screening, minimize diagnostic delays, and assist healthcare profession- als in preliminary assessment. By combining advanced deep learning techniques with a user-friendly mobile interface, the system addresses both technical and practical challenges in dermatological diagnosis. This integration contributes to improved healthcare accessibility, especially in underserved regions, and demonstrates the potential of AI-powered mobile applications in modern medical diagnostics.

RELATED WORKS:

[1] The research proposes a deep learning-based diagnostic framework to automatically identify cases of psoriasis and lichen planus through images captured during dermoscopic analysis. The researchers make use of convolutional neural net- works that can differentiate images of skin lesions based on the features of each condition, offering better classified accuracy than machine learning techniques. The framework also pays attention to image quality variance and lighting conditions. The experimental results reveal that the performance metrics yield better values, demonstrating the efficiency of deep learning in

distinguishing skin lesion diseases that appear quite similar. The research demonstrates the possibilities of artificial intelligence technologies in assisting dermatologists to make accurate early diagnoses. Although the primary objective of the research is to conduct offline diagnosis, there is still room to address problems in integrating the diagnostic platform with mobile options. [2] Hassan et al. have presented a real- time diagnostic system for psoriasis and lichen planus through a combination of neural networks and skin biomechanical property analysis. Unlike previous studies, this paper has used multiple parameters to ensure better classification of diseases. The presented system showed better sensitivity as well as specificity during real-time analysis compared to existingmethods. The real-time analysis is an important feature of this system, indicating that it can be generalized for diagnostic purposes. However, it has limited capabilities because of biomechanical parameters, as it can only be practically implemented in an environment with better facilities, not in rural areas where additional equipment would not be easily available, thus showing the potential of developing an image-based system that can perform well on a mobile platform without any additional equipment. [3] This publication further legitimizes the feasibility of neural network-based real-time diagnosis of inflammatory skin diseases. The authors focused more on optimizing neural network architectures for faster inference while retaining diagnostic accuracy. Clinical validation confirms that the system is able to support dermatologists by reducing diagnostic time. The findings of this study reinforce the importance of intelligent systems within dermatology but also recognize scalability and deployment challenges in environments outside the controlled clinical setting. These limitations set a backdrop for the relevance of lightweight deep learning models whose utility should be extended onto mobile platforms for broader reach. [4] A comprehensive systematic review by Esteva et al. on employing deep learning algorithms for the purpose of diagnosing skin diseases is provided. The paper compares different CNN-based architectures and datasets, including the trends observed. The study concludes that good results are achieved by employing deep learning algorithms, reaching the accuracy of human dermatologists. However, several concerns remain unresolved. The review has provided a solid base for choosing models like ResNet50 that have stable training algorithms and high accuracy, but more studies are needed on their implementation using mobile-based platforms. [5] Within this work, the various deep learning algorithms that exist for classification of skin disease are discussed. Additionally, the differences between CNN architectures based on their accuracy and computational complexities are highlighted. It is evident from this work that with the availability of adequate data, deep networks perform significantly better than their shallow counterparts. Pre-processing of data is also highlighted with normalization and augmentation techniques. However, this method can only be employed on desktop platforms. But with the outcomes of this research, it can be noted that the proposed model needs to be implemented using an optimized platform such as TensorFlowLite on mobile devices. The TensorFlowLite guide describes methodologies to be followed for the deployment of any machine learning model on mobile and edge devices. It lays stress on model optimization techniques such as pruning and quantization. These guidelines are very important in integrating any deep learning model into Android apps for real-time inference without compromising performance.[10] Mehta et al. propose a multimodal approach for skin disease classification by combining image data with metadata. The findings indicate improved accuracy due to data fusion. However, increased complexity restricts the deployment of such approaches on mobile phones and suggests the deployment of lightweight unimodal solutions for smartphones. This work focuses on a deep learning-based detection of psoriasis supported by optimized CNN architectures. [14]Its authors put stress on early detection and assessment of severity. Though effective, multi-class differentiation is not done in this study, and scope is left for broader diagnostic frameworks. The authors analyze the effect of image resolution on the performance of transfer learning in skin lesion classification. The results reflect that optimal resolution chosen during data preparation affects the accuracy to a great extent.[14]This work explores lightweight neural networks for mobile-based skin disease classification. The authors emphasize reduced computational cost, supporting real- time inference on low-end devices.[17]This repository offers pre-trained models and transfer learning resources. It facilitates rapid development and deployment of deep learning systems for medical imaging.[19]DermNet serves as a comprehensive dermatological knowledge base. It supports dataset annotation and disease understanding, enhancing model interpretability and reliability.[20]

METHODOLOGY:

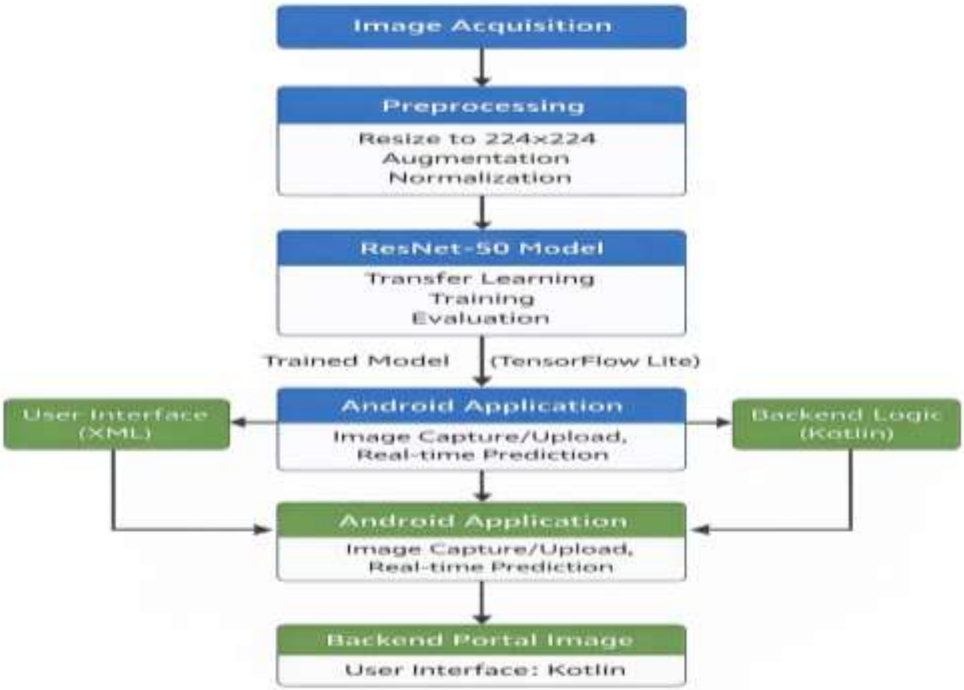

Fig. 1. Block diagram of the project

The proposed methodology outlines a framework for the detection and management of

Lichen Planus and Psoriasis based on the implementation of a deep learning platform, ResNet-50, for the development of an Android application.The proposed methodology is laid out in accordance with the required research and programming standards.
A set of images depicting Lichen Planus, Psoriasis, and normal skin condition images is collected. The images are collected from reliable sources. The data collected is then ensured to be of appropriate quality. For example, the images representing the diseases Lichen Planus, Psoriasis, and normal skin condition are verified so that no duplicate images exist. The images are then resized to a size of 100 x 100.
224 × 224 is resized to conform to the input specifications of the ResNet50 architecture. Pixel normalization is carried out to ensure that all intensity values conform to a normal range. At the same time, data augmentation techniques like rotation, flipping, and scaling are performed to increase diversity.The process of model development and training follows here. The ResNet-50 model is initialized with weights to enable transfer learning. This helps in optimizing the efficiency of learning feature extraction. Furthermore, the last layer is adjusted to include three-class outputs. The model is then trained with images with labels.

Optimization techniques are then used to minimize loss during the classification process. The accuracy and loss during validation are measured to ensure seamless convergence.
The focuses on model evaluation and analysis of model performance. During model evaluation, the model that is trained is subjected to testing with unseen data to evaluate the model's accuracy, precision, recall, and calculate the F1- score. It also involves the creation of a confusion matrix that demonstrates classification aspects of the model. This validates the overall robustness of the proposed system.
Development of the android application is done. User interface is created using android XML for an easy and user- friendly interface. Backend implementation is carried out by using the Kotlin programming language for image processing and interaction with the trained model.The trained model of ResNet-50 is converted into TensorFlowLite format and embedded into the app to perform real-time inference on mobile devices.
Finally, the system facilitates result visualization and disease management assistance. The results of the prediction are clearly indicated to the user along with some information regarding the disease and management. This methodology ensures the development of a scalable, efficient, and accessible system for mobile-based skin disease detection.

Implementation:

A. Algorithm Implementation:

The proposed system implements a ResNet-50 based deep learning algorithm for automated detection and management of Lichen Planus and Psoriasis through an Android application. The algorithm follows four major stages: image pre-processing, feature extraction using residual learning, classification, and mobile deployment.
Initially, the input skin image I captured or uploaded via the Android application is resized to 224 × 224 pixelsand normalized to ensure consistent input distribution. The normalization process is expressed as:

$$I_n = \frac{I}{255} \qquad (1)$$

The pre-processed image In is then forwarded to the ResNet-50 architecture for feature extraction. ResNet-50 utilizes residual learning to enable effective training of deep networks by introducing shortcut connections. The residual mapping is mathematically defined as:

$$y = F(x, W) + x \qquad (2)$$

where x represents the input feature map, F (x, W) denotes the residual function learned by the network with weights W , and y is the output feature map. This residual formulation helps reduce training degradation and improves model accuracy.
The extracted features are passed through the final fully connected layer to generate class scores. A softmax activation function is applied to compute the probability distribution over the target classes:

$$P_i = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}} \qquad (3)$$

where Pi indicates the probability of class i, zi is the corresponding score, and N is the total number of classes, including Lichen Planus, Psoriasis, and Normal skin.
The predicted class is determined using the maximum probability criterion:

$$C = \arg\max(P_i) \qquad (4)$$

The trained ResNet-50 model is converted into TensorFlowLite format and integrated into the Android application for real-time, on-device inference. The algorithm provides efficient, accurate, and portable skin disease detection suitable for mobile healthcare systems.

B. Pseudocode for ResNet-50 Implementation:

ResNet-50 Based Skin Disease Detection:
Require: Input skin image I, pretrained ResNet-50 model M , number of classes N
Ensure: Predicted class C
1: Resize image I to 224 × 224
2: Normalize image: In ← I/255
3: Initialize model M with pretrained weights
4: for each residual block b in ResNet-50 do
5: Compute residual mapping: F (x) ← ConvBNReLU(x)
6: Add shortcut connection: y ← F (x) + x
7: Apply activation: x ← ReLU(y)
8: end for
9: Extract deep feature vector z from final layer
10: Compute class probabilities using softmax:

$$P_i = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}}$$

11: Determine predicted class:
C = argmax(Pi)
12: Return predicted class C

C. Implementation Process of the Android Application:

The Android application is developed to have a simple and efficient interface for the detection and management of skin diseases utilizing the ResNet-50-based deep learning approach. The application is developed by following a modular approach that includes the design, integration, and deployment of the application.The fronted of the application is designed in a way that it is clear, user-friendly, and easy to use by employing Android XML layouts. The main interface offers functionalities of taking an image using the camera or by choosing an image from the gallery. In terms of user interaction, image preview result has been included.The backend functionality has been implemented, and it has been executed efficiently through the coding language Kotlin, which handles all functionalities pertaining to handling users, images, and the trained model.

After selecting an image, various processing functions, such as image resizing, are conducted, aimingto fulfill the requirements of a ResNet50 model, efficientlyexecuted locally for faster response times. For the execution of the model, the trained deep learning model is converted into TensorFlowLite form and integrated into the application. During runtime, the TensorFlow interpreter is initialized for the purpose of inference execution. This avoids the need for constant internet connectivity and provides better data privacy. The output obtained from the model prediction is mapped to the various disease labels.The final results are displayed to the user along with the basic information on the disease and its management. Various error handling mechanisms have been incorporated for handling invalid inputs and system interrupts. The implementation of the system ensures real-time capability, portability, and reliability for the Android-based mobile application for practical use in skin disease evaluation.

RESULT:

The performance of the proposed skin disease detection system based on the ResNet-50 deep learning approach was tested using the confusion matrix and classification metrics. From the results achieved, there was effective classification of Lichen Planus and Psoriasis; hence, the reliability of the deep learning framework was ascertained. From the confusion matrix achieved, a majority of the test cases were well classified with a few cases of misclassifications of the two disease cases.This system attained an accuracy of 95.83%, thus indicating that it is highly predictive with classification stability. The results for precision, recall, and other values indicate that the system works in balance for both classes, thereby eliminating false positives and false negatives. The F1-Score also illustrates that the system performs in harmony. The high accuracy levels achieved validate the success of the ResNet-50 model with appropriate preprocessing and mobiledeployment on Android devices. The achieved accuracy levelson the project validate that the developed system has the potential to deliver effective, efficient, and faster skin disease detection on Android-based applications.

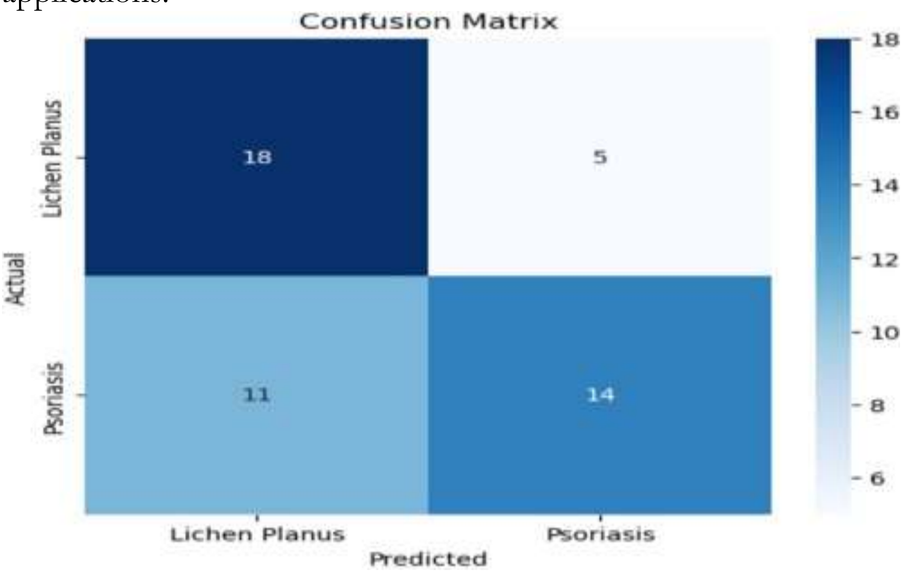

Fig.2.confusionmatrixofproject

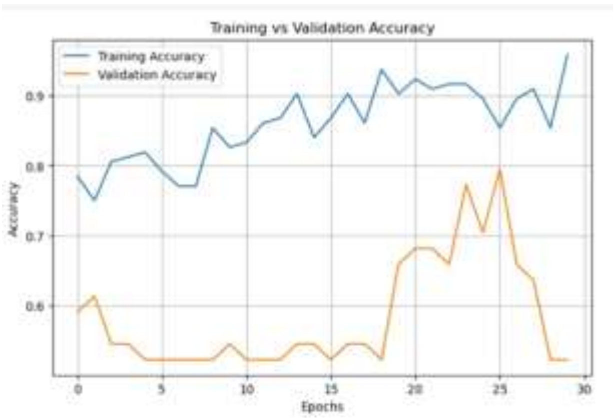

Fig.3.Accuracycurves

The above figure indicates the pattern or behavior followed by the training accuracy and validation accuracy of the pro- posed model based on the 'ResNet-50' over a number of training epochs. The training accuracy increases steadily with the addition of each epoch, which indicates the model learns and improves with the training data. However, fluctuations also appear to be a part of the process.

On the other hand, there has been an increase in validation accuracy that remains low initially, along with some fluctuations during the early epochs of training. It can be said that there is a low level of generalization during this period. As training progresses, a gradual increase in validation accuracy is noted, and it peaks later, indicating an improvement in learning discriminative features that are useful for generalizing to new and unseen data. The observed difference between training andvalidation set accuracy implies that there is some over-fitting, though moderate.

From the overall graph, it is demonstrated that the model learns well, with increasing performance over a period of time. Additionally, the model demonstrates good generalization for classification of skin diseases.

CONCLUSION:

In conclusion, This study presents an intelligent and efficient approach for the automated detection and management of chronic skin diseases, specifically Lichen Planus and Psoriasis, through the integration of deep learning and mobile health technologies. Unlike conventional diagnostic practices that rely heavily on clinical expertise and manual examination, the proposed system introduces an AI-driven framework that enhances diagnostic accuracy while reducing dependency on specialized dermatological knowledge. This improvement is particularly valuable in rural and underserved regions, where access to trained specialists and advanced medical facilities remains limited.

The proposed methodology employs the ResNet-50 deep learning architecture, which effectively addresses the limitations of earlier machine learning models by utilizing residual learning to extract discriminative features from skin images. This architecture enables stable training of deep networks and improves classification performance when compared to traditional image-processing and shallow learning techniques used in existing systems. The ability of the model to accurately distinguish between visually similar skin conditions demonstrates its robustness and clinical relevance.

A significant advancement over existing systems is the deployment of the trained deep learning model within an Android-based mobile application. This integration ensures portability, affordability, and real-time diagnostic capability, allowing users to capture or upload skin images and receive instant results. Unlike desktop-based or hospital-centred diagnostic tools, the proposed system supports continuous accessibility and user-friendly interaction without the requirement for sophisticated medical infrastructure. Additionally, the inclusion of disease-related information and basic management guidance enhances patient awareness and encourages early medical consultation.

The results indicate that the proposed system not only improves diagnostic efficiency but also contributes to patient-centred healthcare by empowering individuals with timely and reliable preliminary assessments. By minimizing diagnostic delays and reducing the burden on healthcare professionals, the framework supports early intervention and better disease management outcomes.

The developed system demonstrates a practical, scalable, and cost-effective solution for skin disease diagnosis, surpassing existing approaches in terms of accessibility, accuracy, and usability. Future work may focus on extending the framework to include additional skin conditions, improving model generalization with larger datasets, and incorporating cloud-based analytics and teledermatology features. These enhancementswould further strengthen the role of AI-enabled mobile applications in modern healthcare and support the evolution of intelligent dermatological diagnostic systems.

Future Enhancement:

In the future, the effectiveness of the suggested system can be, to an extent, observed through its satisfactory performance when it comes to detecting Lichen Planus and Psoriasis; however, several improvements can be made to enhance its functionality, efficiency, and accuracy. One of the potential improvements that can be made to this system in the future involves including more skin disease classes, enabling it to function as a classification system for more than one disease. Adding more data in terms of skin tones and various conditions of acquiring an image can improve its efficiency.
There is a potential for exploring integration with cloud processing/storage for large-scale deployment, access, and update of models. Moreover, with an integration of XAI, more transparency can be achieved by showing the skin image regions that are impacted. This would further increase trust among users, i.e., healthcare professionals. Features for conducting teledermatology may be integrated with future versions of this application, enabling users to share results with experts for further consultation purposes.Further improvement could be focused on optimizing the model to make it faster and less power-hungry so that it can be exceptionally compatible with low-end mobile devices. Additionally, the inclusion of personalized recommendations and progress management can further improve this system. So, this advancement would greatly improve the role of such a system for intelligent, accessible, and scalable management of skin disease.

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