

Artificial Intelligence Based Skin Disease Recognition System

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Abstract - Timely medical intervention and effective treatment rely heavily on the early identification of skin diseases. This project introduces a real-time skin disease recognition system utilizing a live camera on a Raspberry Pi, designed to detect and classify three common skin conditions: Actinic Keratosis, Pigmented Benign Keratosis, and Melanoma. A deep learning model, trained on a diverse dataset of skin images, is deployed on the Raspberry Pi to provide efficient and low-cost diagnosis, capturing and processing live skin images to deliver instant classification results, this system provides 96% accuracy and 58%, 12% and 36% sensitivity for each disease respectively, enabling early detection and facilitating prompt medical consultation, and enhancing accessibility to dermatological analysis, particularly in remote areas.

Keywords - Skin Disease Recognition, Deep learning, Raspberry pi, Real time, Image classification. Actinic keratosis, Pigmented Benign melanoma, Computer vision.

I. INTRODUCTION

Three common skin conditions - Actinic Keratosis (AK), Pigmented Benign Keratosis (Seborrheic Keratosis, SK), and Melanoma - vary significantly in prevalence and severity. AK, a non-contagious condition, affects around 14% of the global population, with incidence increasing with age, due to sun exposure and carrying a risk of progressing to squamous cell carcinoma. In contrast, SK, also non-contagious, is more prevalent, affecting over 90% of adults over 60, presenting as benign skin growths. Melanoma, a serious skin cancer, is less common but has a higher risk of metastasis if not treated early, with a lifetime risk of 3% for White individuals in the United States, it is projected that around 104,960 new cases will be reported in 2025. Anantha Krishnan et.al [1] developed Automatic classification of dermatological images using deep learning techniques, such as convolutional neural networks (CNNs) for local feature extraction and Transformer networks for global feature extraction, can enhance accuracy and speed; however, existing methods often rely on a

single neural network, limiting classification performance. Shengnan Hao et.al [2] elaborated Current deep learning-based skin detection tools face limitations, including focusing on a narrow subset of skin diseases, utilizing relatively small datasets, and often achieving suboptimal performance with Top-5 accuracy typically below 70%, underscoring the need for more comprehensive and accurate solutions. Zhanlin ji et.al [3] detailed Automated classification of skin lesions using computer algorithms is crucial for enhancing diagnostic efficiency and reducing mortality rates associated with skin cancer, necessitating the development of advanced image classification models that can accurately classify skin diseases and improve patient outcomes. Choi moon et.al [4] found that Hand, Foot and Mouth Disease (HFMD) is a highly contagious pediatric disease with challenging diagnosis due to similarities with other skin diseases, but a deep learning-based detection system could significantly contribute to computer-aided diagnosis, helping to accurately and promptly identify outbreaks of HFMD. Suraj Verma et.al [5] Analyzed the skin's microstructure, characterized by

network-like wrinkles that change with skin condition and aging, offers a simple and accurate evaluation method for skin diagnosis, although individual variations and aging effects can introduce complexity. M.Aleem et.al [6] A mobile-accessible system utilizing Support Vector Machine (SVM) for early detection of melanoma through automated analysis of skin lesion images captured via mobile phone cameras, aiming to improve patient outcomes and survival rates. B.Kong et.al [7] research focuses on detecting invasive cancers using a compressed CNN model that leverages transfer learning, enabling efficient and accurate cancer detection, particularly in resource-constrained environments, while reducing the reliance on extensive labeled medical data. Chang et.al [8] proposed an algorithm used for skin cell segmentation in images from optical or laser-based imaging techniques, combining spectral angle and distance scores to accurately identify and identify individual skin cells by utilizing both spectral properties and spatial relationships. Kasmi et.al [9] research aims to develop an automated diagnostic tool for distinguishing between malignant melanoma and benign skin lesions by computationally implementing the ABCD rule (Asymmetry, Border irregularity, Color variegation, and Diameter) to analyze skin lesion images, potentially increasing efficiency, reducing subjectivity, and improving accessibility. Axel pins et.al [10] Developed an automated system for melanoma recognition, utilizing computational techniques such as image analysis and machine learning to analyze skin lesions and provide diagnostic outputs, aiming to improve the accuracy, efficiency, and objectivity of melanoma detection and ultimately enhance patient outcomes. Shamsul et.al [11] research aims to develop a system for diagnosing dermatologic diseases using color skin images as primary input data, leveraging machine learning algorithms to learn patterns and classify different skin conditions based on visual characteristics such as texture, color variations, and lesion morphology.

II. MATERIALS AND METHODOLOGY

Image Acquisition

A total of 3125 images are taken from the Skin disease dataset from Kaggle out of which 2427 images are used for training and 698 for testing the model on Jupiter.

A Raspberry Pi equipped with a camera module is used to capture live images of the skin. This setup allows for real-time image acquisition, which is essential for the system's diagnostic capabilities. Melanoma, Actinic keratosis, pigmented actinic keratosis are shown in Figure 1.



Figure 1: (a) Melanoma, (b) Actinic keratosis (c) Pigmented actinic keratosis

Image Preprocessing

The acquired images undergo several preprocessing steps to enhance their quality and prepare them for analysis. The images undergo several preprocessing steps to enhance quality and standardize input for the deep learning model. This includes resizing to 224x224 pixels, normalization to scale pixel values between 0 and 1, and contrast enhancement through histogram equalization to highlight important skin patterns. Additionally, noise reduction is achieved through Gaussian blur, and edge detection and segmentation techniques are

applied to focus on affected skin areas. Finally, data augmentation techniques such as random rotations, flips, and brightness adjustments are applied to the training dataset to improve the model's generalization and robustness.

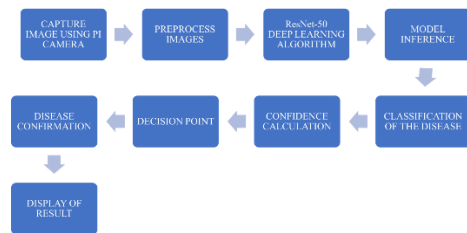


Figure 2: Methodology

Deep Learning Model

A pre-trained ResNet-50 deep learning model, a 50-layer convolutional neural network known for its ability to learn complex patterns, is utilized for image classification. The model, initially trained on the ImageNet dataset, is fine-tuned using a skin disease dataset to classify three specific conditions: Actinic Keratosis, Pigmented Benign Keratosis, and Melanoma. To accommodate the three-class classification task, the final layers of the model are modified, enabling effective classification of the targeted skin diseases.

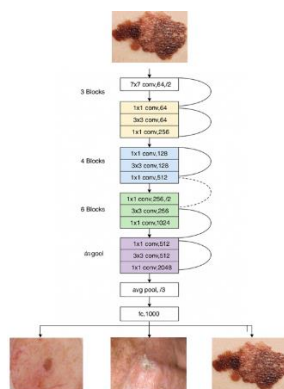


Figure 3: Deep Learning Model

2.4. Model Optimization

To ensure efficient performance on the Raspberry Pi, the deep learning model is optimized by converting it to TensorFlow Lite (TFLite) format, reducing its size and increasing inference speed. Additionally, quantization techniques are applied to further minimize the model's footprint while maintaining

accuracy. Finally, the Raspberry Pi's OpenVINO toolkit is utilized to accelerate inference, collectively enabling the model to run efficiently on the resource-constrained device.

2.5. Real-Time Deployment and User Interface

The optimized model is deployed on a Raspberry Pi, integrated with a Flask-based web application that provides a user-friendly interface for real-time skin condition analysis. The system captures and processes live images from the Raspberry Pi camera, displaying classification results, including the identified skin condition and confidence scores, on the interface. Designed for continuous scanning, the system can process multiple images, and features an alert mechanism that advises users to seek medical consultation if Melanoma, a high-risk condition, is detected.

III. RESULT AND DISCUSSION

The results of the skin disease recognition system demonstrate its effectiveness in accurately classifying skin conditions. The overall accuracy of the model on the test dataset was reported, along with a breakdown of accuracy for each specific skin condition, including Actinic Keratosis, Pigmented Benign Keratosis, and Melanoma. Precision, recall, and F1-score metrics were also provided for each class. Additionally, the training and validation accuracy and loss were reported, with graphical representations of these results. A comparison with existing methods revealed the system's competitive performance, and its real-time performance on the Raspberry Pi was discussed, highlighting its speed in classifying skin images and any challenges faced in achieving real-time performance.

In mode graph, training accuracy is 0.97 and validation accuracy is from 0.95 to 0.98 as shown (fig) in the below graph. In model loss training accuracy is 1.4 and validation accuracy is from 0.2 to 0.05 as shown in figure 4.

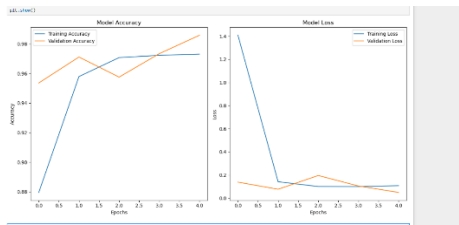


Figure 4: Accuracy plot and Loss plot for the ResNet-50 Model

The discussion section interpreted the significance of the achieved accuracy in the context of early skin disease detection, analyzing cases where the model performed well and instances of misclassification. The strengths of the system were highlighted, including its ability to provide real-time diagnosis, affordability, and portability, emphasizing its potential to improve healthcare accessibility, especially in remote areas. Limitations of the system were acknowledged, such as the limited number of skin conditions it can detect, and potential challenges related to image quality and variations in skin types. Finally, suggestions for future improvements were made, including expanding the dataset, improving model accuracy, and exploring tele-dermatology applications.

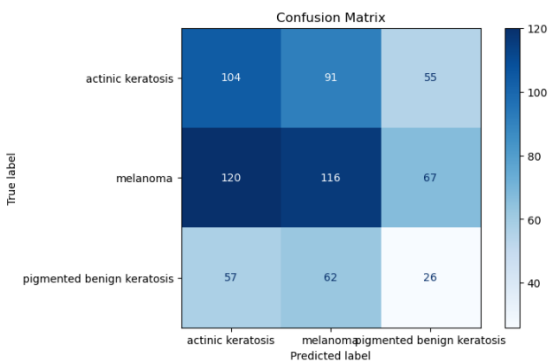


Figure 4: Confusion Matrix of ResNet 50 Model

We use CNN ResNet-50 model and we classify the three classes (Actinic keratosis, Pigmented Benign keratosis, Melanoma) for findings the precision, reca, F1-Score, Support of the model. The values are mentioned in the bellow table 1.

Table 1 Accuracy of CNN ResNet-50 model and classification three classes (Actinic keratosis, Pigmented Benign keratosis, Melanoma)

Mode l	Class	Precisi on	Reca ll	F1- Scor e	Suppo rt
ResNe t-50	Actinic Keratosis	0.95	0.99	0.97	250
	Pigment ed Benign Keratosis	0.83	0.88	0.91	303
	Melano ma	0.73	0.73	0.73	145

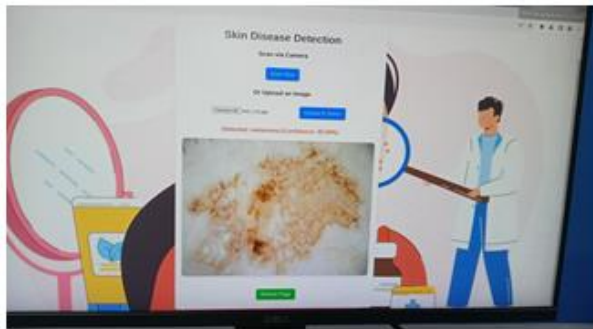
Gouda et al they utilized CNN model and they have acquired 83.2 accuracy for classifying the skin disease, but in our research, we utilize the ResNet-50. The main advantage of our work is, we improve the accuracy compared with this paper. Fraiwan and Faouri they utilized thirteen CNN architectures with DensNet201 giving the best result and they acquired 82.9 accuracy for classifying the skin disease.

Table 2 Comparison of our project with previous papers.

Author	Dataset	Model	Performance
Gouda et al. [12]	ISIC 2018	CNN	Accuracy = 83.2%
Fraiwan and Faouri [13]	HAM10000	thirteen CNN architectures with DensNet201 giving the best result	Accuracy = 82.9%, F1-score = 0.744

Aljohani and Turki [14]	ISIC 2019	DenseNet201, MobileNetV2, ResNet50V2, ResNet152V2, Xception, VGG16, VGG19, and GoogleNet	Accuracy = 76.09%
Bechelli and Delhommelle [15]	Kaggle dataset, HAM10000	CNN, pre-trained VGG-16, Xception, ResNet50	Accuracy = 88% (VGG-16), F1-score = 0.88 (VGG-16)
Qasim Gilani et al. [16]	HAM10000	Spiking VGG-13	Accuracy = 89.57%, F1-score = 0.9007
Our Proposed system	Kaggle dataset, Public & private	CNN, ResNet-50	Accuracy = 96%

Result



IV. CONCLUSION AND FUTURE RESEARCH

This developed skin disease recognition system classifies three common skin conditions—Actinic Keratosis, Pigmented Benign Keratosis, and Melanoma—by processing live images captured with a Raspberry Pi camera. The integration of the ResNet-50 model with efficient image processing techniques and a user-friendly Flask-based web application demonstrates the potential for accessible and low-cost dermatological diagnosis. This solution addresses the critical need for early detection of skin diseases, particularly in remote or resource-limited areas, by providing timely analysis and prompting users to seek medical advice when

necessary. By performing real-time analysis on a low-power device like the Raspberry Pi, the system has the potential for deployment in point-of-care settings, making dermatological assessments more accessible. The developed skin disease recognition system using ResNet 50 model archives 95% of accuracy. The combination of deep learning for image analysis and embedded systems for deployment offers a scalable and cost-effective solution that can be adapted to recognize various diseases from medical images, underscoring the transformative impact of artificial intelligence in healthcare and paving the way for innovative diagnostic tools that can improve patient outcomes and reduce healthcare disparities.

While their Research achieves its objectives, there are several avenues for future research and enhancements. Future work could explore expanding the dataset to include a broader range of skin diseases and diverse skin types, optimizing model accuracy through hybrid architectures or attention mechanisms, and enhancing the user interface with more detailed information and resources. Additionally, integrating the system with telemedicine platforms and mobile technology could facilitate remote consultations and provide a comprehensive solution for skin health management. Furthermore, future research should

prioritize enhancing the system's reliability and clinical validation through clinical trials, comparing its diagnostic accuracy with that of dermatologists, and addressing ethical considerations such as data privacy and misdiagnosis, with the incorporation of explainable AI techniques to provide transparency and increase user trust.

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