SKIN DISEASE DETECTION USING CONVOLUTIONAL NEURAL NETWORK WITH RASPBERRY PI

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Abstract

Skin disease detection is a core area in medical diagnosis since timely and precise diagnosis of skin conditions has a substantial impact on the success of treatment. Conventional techniques involving direct visual examination by dermatologists or traditional image processing methods are plagued by issues like subjectivity, expense, and lack of access in rural locations. To overcome such limitations, the proposed model formulates a deep convolutional neural network with skin disease detection system using Raspberry Pi (CNN based Raspberry Pi model). By exploiting the strong feature extraction properties of deep CNN and portability and affordability of Raspberry Pi, the proposed CNN based Raspberry Pi model presents a cost-effective, scalable, and accessible solution for early diagnosis of skin disease, especially in rural and underserved areas.

Keywords: *Skin disease detection, Convolutional Neural Network, Raspberry Pi, Medical diagnostics, disease identification.*

1. Introduction

Skin diseases are among the most prevalent health conditions occurring in humans across the globe, from mild in nature such as acne and eczema to serious disorders such as melanoma and psoriasis [1-5]. Early treatment and detection help to avoid complications, particularly for skin cancers where early diagnosis is a matter of life and death. As dermatological diseases are on the rise and there is a lack of specialists in most areas, particularly rural and undeveloped parts, there is a need for fast, accurate, and affordable automated skin disease diagnosis systems [6-7] .

Current automated skin disease diagnosis systems, though, tend to have major limitations. Many demand high-performance computing resources and are unable to run efficiently in real-time or on low-cost portable hardware. Also, certain systems rely greatly on high-resolution images and sophisticated preprocessing steps, which restrict their application in real-world, low-resource environments [8-10].

The primary objective of the CNN based Raspberry Pi model is to create an effective, precise, and portable skin disease diagnostic system through the integration of deep CNN with the low-cost Raspberry Pi module. This method facilitates real-time classification of different skin diseases using image input with minimal computational resources. This proposed system overcomes central limitations of the current models in terms of being highly hardware demanding, having less accessibility, and depending on human diagnostics by presenting a light solution that is autonomous and can be implemented in isolated or resource-deprived environments.

2. Literature Review

Siegel et al. [1] develops epidemiological information on cancer in the United States, highlighting increasing skin cancer incidence. Its strength is providing a general, data-based platform for public health information. It does not have diagnostic or computational methods, though, and so cannot be applied to ML model construction. Rogers et al. [2] have estimated the burden of non-melanoma skin cancers from national epidemiological images. It presents stable, population-based data appropriate for public health planning. The disadvantage lies in its unavailability as a diagnostic or algorithmic input due to a lack of algorithms. Galvez et al. [3] implemented machine learning to multi-platform integrated microarray and RNA-seq data to find skin cancer biomarkers. It enhances diagnostic accuracy via multi-platform genomic integration. Nonetheless, its dependency on high, complicated molecular data hinders its applicability in clinical or low-resource environments. Sharma et al. [4] introduce a cascaded ensemble network model of CNNs and handcrafted features for skin cancer classification. The network attains dermatologist-level performance and good generalization to a wide range of lesion types. However, its computational and training complexities restrict real-time diagnosis application. Gu et al. [5] developed domain shift in skin disease classification with progressive transfer learning and adversarial domain adaptation. The model is quite adaptable to diverse clinical settings and unseen data, improving real-world applicability. The method entails computationally expensive adversarial training, however, confining application in low-resource settings.

2.1 Challenges

- Lack of integration with machine learning or image-based methods restricts their applicability in real-world clinical diagnostics [1].
- Takes molecular-level information, which is costly and not available in routine clinical environments [2].
- Integration and preprocessing of heterogeneous genomic data require high computational power and expertise [3].

3. Proposed Methodology

The proposed CNN based Raspberry Pi model aims to identify skin illnesses through the use of CNN method that are implemented on a Raspberry Pi. The workflow starts with gathering data from a skin disease data set, in Kaggle, consisting of images of different skin ailments. Such images are processed with preprocessing actions like resizing, normalization, and augmentation to support improved model performance and consistency. The preprocessed images are then fed into the VGG16 model for feature extraction, taking advantage of its capability to learn high-level visual patterns. The extracted features are then classified by a CNN to identify the particular type of skin disease, thus making this an effective and lightweight solution for real-time skin disease diagnosis on edge devices such as the Raspberry Pi. Figure 1 shows the architecture of CNN based Raspberry pi model.

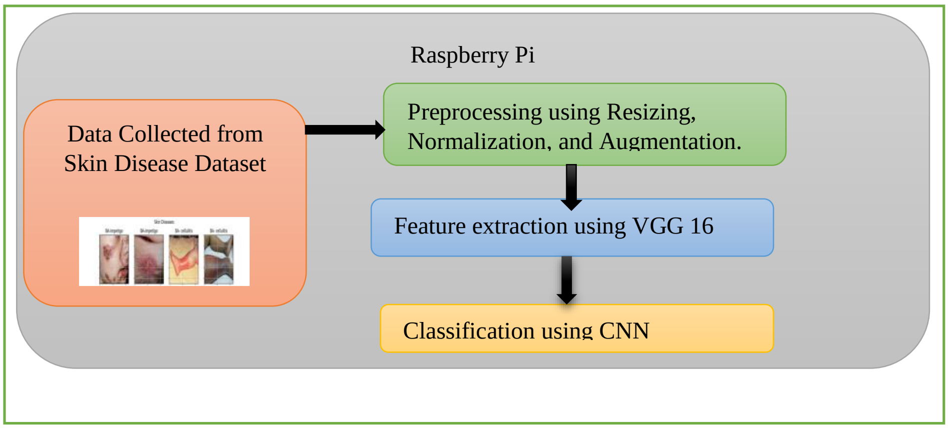


Figure 1: Architecture for proposed CNN based Raspberry Pi model

3.1 Data Collected from Skin Disease Dataset

The skin disease dataset (https://www.kaggle.com/datasets/kmader/skin-cancer-mnist-ham10000) from Kaggle consists of 10,015 labeled dermatoscopic images of seven skin disease classes. It is used to support supervised learning with rich demographics and lesion varieties for more generalization. Its balance and quality make it suitable for training deep learning models for skin disease classification.

3.2 Preprocessing using Resizing, Normalization and Augmentation

In this research, the input for pre-processing is directly obtained from the skin disease dataset. Resizing is utilized to normalize all images to a uniform dimension suitable for the VGG16 model. Normalization is utilized to scale pixel values, usually between 0 and 1, to enhance efficiency in training the model. To boost dataset diversity and alleviate overfitting, data augmentation methods like rotation, flipping, and zooming are utilized. These preprocessing operations assure that the model is provided with clean, consistent, and diverse input for strong learning.

3.3 Classification Using Convolutional Neural Network

This research utilizes the VGG16 model to feature extraction of skin images using max-pooling after every convolutional block for optimization. The feature maps are flattened into a one-dimensional vector through a fully connected layer for classification. A Softmax activation function is used in the output layer to classify images as normal or cancerous. This pipeline allows efficient and accurate skin cancer detection from dermatoscopic images.

4. Result and Discussion

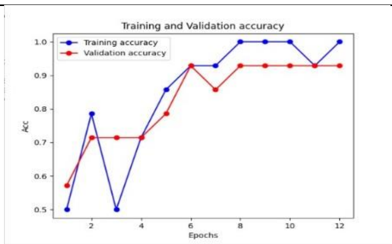
4.1 Dataset Description

4.1.1 Skin disease dataset:

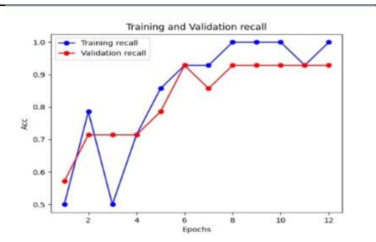
The Kaggle HAM10000 dataset comprises 10,015 labeled dermatoscopic images distributed over seven skin disease classes. It is favorable for supervised learning with various demographics and lesion classes for enhanced generalization. Its balance and quality make it optimal for training deep learning models on skin disease classification.

4.2 Performance Analysis

Figure 2 illustrates that the model reached 95% accuracy and 90.8% recall, which implies high overall performance in skin image classification. High accuracy indicates right predictions for both classes, and high recall implies its sensitivity in detecting cancer. These two statistics together prove the model's dependability and performance in medical image classification. Table 1 demonstrates the training and validation performance of the CNN based Raspberry Pi model over 12 epochs, with important evaluation measures, accuracy and recall.



a) Accuracy



b) Recall

Figure 2. Performance evaluation of proposed CNN based Raspberry pi model, a) Accuracy, b) Precision

Table 1: Performance Evolution Table

Epoch	Training Accuracy (%)	Validation Accuracy (%)	Training Recall (%)	Validation Recall (%)
7	100%	90%	100%	90%
8	100%	93%	100%	93%
9	100%	93%	100%	93%
10	93%	93%	93%	93%
11	94%	93%	94%	93%
12	95%	93%	95%	93%

4.4 Training and Validation Loss:

Figure 3 illustrates the training and validation losses over 12 epochs and how the performance of the model improves while training. At first, both losses are high, with the training loss declining steeply, and validation loss fluctuating before tending to decrease progressively. From approximately epoch 6 onwards, both losses remain constant at low rates, showing that the model is learning well without a considerable amount of overfitting.

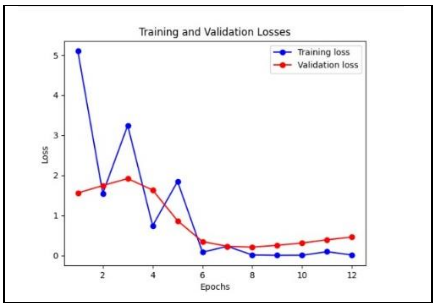


Figure 3. Training and Validation Loss

4.5 Confusion Matrix Analysis

Figure 4 demonstrates a confusion matrix for a binary classifier where the actual values are plotted against the predicted values. It demonstrates that the model correctly predicted 6 samples of class 0 and 7 samples of class 1. It made a single false positive by mislabeling a sample of class 0 as class 1, and no false negatives. It performs high due to detection of class 1, with overall high accuracy and little misclassification.

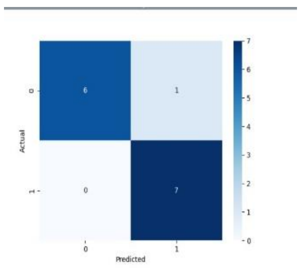


Figure 4. Confusion Matrix Analysis

5. Conclusion

The Proposed CNN based Raspberry pi model for detecting skin disease with CNN on Raspberry Pi gives an effective and low-cost approach for early skin condition diagnosis. With the utilization of a model and optimizing it for edge use, the system ensures high accuracy, quick inference, and reduced resource usage. The combination of image preprocessing, feature extraction, and classification into a small and portable device makes it ideal for real-time screening, particularly in remote or resource-poor environments. Overall, this model shows strong potential for facilitating dermatological diagnosis and improving access to skin health monitoring.

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6.1 Journal Article

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