

Intelligent Multi Class Skin Disease Detection System

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Abstract— Skin diseases impact millions of people worldwide, covering diverse demographic groups and represent a substantial public health issue. In order to effectively treat and manage skin disorders, prompt and accurate diagnosis is essential. Deep learning algorithms have accelerated the development of computer aided diagnosis systems, allowing for extremely accurate automated interpretation of medical images. Integrating these algorithms with Raspberry Pi gives medical professionals a low cost, portable way to diagnose patients in real time especially in places with limited resources and access to advanced medical technology. The objective of the proposed research work is to address the problem of multiclass skin disease detection, in which a system is trained to simultaneously distinguish between multiple skin disorders. Multiclass classification involves detecting a wide range of dermatological conditions such as psoriasis, eczema, and melanoma, in contrast to binary classification tasks that distinguish between healthy and diseased skin. The suggested system intends to offer dermatologists and primary care physician comprehensive support in accurately diagnosing a wide range of skin disorders by expanding the scope of detection. It combines deep learning methods with an intelligent embedded system that makes use of a Raspberry Pi to automatically categorize various skin conditions. With the use of an embedded Pi camera and a deep convolutional neural network model, the system is meant to recognize and categorize skin images in real time. Therefore, the suggested work provides an accessible and affordable method of accurately identifying a range of skin conditions. The combination of image processing and machine learning algorithms incorporated in the system enable to classify a number of skin diseases with a high degree of accuracy, enabling prompt diagnosis and treatment.

Index Terms— Convolutional neural network, Raspberry Pi, Deep learning, support vector machine.

I. INTRODUCTION

Skin diseases impact millions of people worldwide, spanning diverse demographic groups, and represent a substantial public health concern. Early and precise diagnosis of skin disorders is essential for efficient treatment and care.

The use of technology in healthcare has changed diagnostic processes recently and provided creative ways to improve and expedite medical treatments. Many conventional machine learning approaches are available for estimating and classifying skin diseases. However, these techniques are ineffective for complex diagnostic requirements in actual practice. Conventional machine learning methods for detecting skin cancer often include obtaining characteristics from images of the disease and then categorizing the features.

Using deep learning models high resolution photographs with millions of pixels results in significant computing costs and additional training time. The versatility and coherence of these approaches must therefore also be taken into account. Numerous research works that describe improvements in the classification of skin diseases have examined the frontier difficulties in the classification of diseases including model robustness, data imbalance, and domain adaptation [1].

Convolutional neural networks (CNNs) have proven to be a highly effective method for the classification of skin lesions. CNN is extremely proficient at evaluating images and can automatically learn hierarchical representations of features from raw pixel data. For classification purposes, it can capture intricate patterns and textures associated with benign or malignant skin lesions. CNNs have good generalization abilities to their training on large datasets and are quite accurate at differentiating between different types of lesions.

One of the limitations of the conventional techniques for disease detection is its perceived inaccuracy in distinguishing between lesions. It might be difficult to distinguish benign from malignant skin infections only by visual inspection, particularly when the lesions are early or have unusual characteristics. The objective of ongoing research and development is to increase the accuracy, efficiency, and accessibility of skin disease detection through the use of technologies including dermoscopy, teledermatology, and computer aided diagnosis systems [2]. Prompt and exact identification of skin disorders is essential for efficient treatment and care. The use of advanced technology in healthcare has transformed diagnostic processes in recent years and has provided creative ways to improve and expedite medical treatments. In this regard, using the Raspberry Pi, as a multipurpose single board computer, offers a promising way to further the diagnosis of skin diseases. In order to investigate the growing field of multi class skin disease detection, the proposed work would integrate Raspberry Pi as an accessible and affordable platform for successful diagnosis [3-4].

The problem of multi class skin disease identification, in which the system is trained to distinguish between numerous skin disorders, is addressed by this proposed work. Multiclass classification necessitates classifying a wide variety of dermatological conditions, such as eczema, psoriasis, melanoma, and acne, in contrast to binary classification tasks that distinguish between healthy and diseased skin. The suggested system intends to offer dermatologists and primary care physician comprehensive support in accurately diagnosing a wide range of skin disorders by broadening its reach of detection. The core contributions of the proposed work are

- Create a model that recognizes different skin conditions from images. This involves imparting a machine learning model to identify and distinguish between several skin problem classifications.
- Implement a system that can process and analyze images is essential for applications in real life, such giving fast feedback to medical professionals.
- An optimization scheme is adapted to estimate the model parameters and ensure that the proposed model operates effectively on the Raspberry Pi, for performance. This results in the creation of a user interface that makes it simple for users to upload images of skin conditions and obtain the classification outcome

II. LITERATURE SURVEY

In [5], a deep learning based automated categorization system that can help doctors identify the type of skin lesion and improve the patient's health is described. It proposes a novel strategy for the categorization of skin lesions utilizing wide Shuffle Net and a new segmentation algorithm. To distinguish the lesion from the background, the skin image's first order cumulative moment (EW-FCM) and entropy based weighting are computed. The HAM10000 and ISIC2019 big datasets are used to assess this approach, which is determined to be appropriate for small systems like mobile healthcare systems. Currently, there are 132,000 occurrences of melanoma skin lesions worldwide each year, while there are about three million cases of non-melanoma skin lesions. Melanoma lesions account for about 80% of skin cancer deaths [6]. In addition to prolonged sun exposure, sunburn history has been associated to the appearance of skin cancer, particularly melanoma. Correct identification of melanoma can enhance patient survival rates in the early grades. The accuracy and effectiveness of the early detection of different kinds of skin disorders can be improved with the use of an automatic classification system [7].

In [8], the twenty one types of skin lesion classification and a four level lesion detection technique are covered. The Google Net model employs a four level arrangement for skin images. Samples that are benign and malignant are characterized first, and then melanocytic and epithelial cells are identified. Bowen, actinic keratosis, seborrheic keratosis, and basal cell carcinoma lesions were also detected by the approach. A novel attention residual network is constructed in [9] by inserting an attention layer at the end of the ResNet architecture. Melanoma, nevus lesions, and seborrheic keratosis are classified using this method. Convolutional neural network based machine learning models are commonly used for automatic lesion disease identification with

great accuracy compared to traditional machine learning techniques. A novel preprocessing method for obtaining the dataset of skin lesion area of interest (RoI) is described in [9]. With two datasets comprising raw and ROI extracted images, the effectiveness of well known CNN classifiers is compared. It has been demonstrated that using ROI extracted datasets to train CNN models can increase prediction accuracy while substantially decreasing the amount of classifier assessment and training time. In [10], an intelligent diagnosis approach is worked out for the multiclass classification of skin lesions. Error correcting output codes (ECOC) support vector machines (SVM) and deep convolution neural networks are used in a hybrid approach to achieve it. The goal of the design, implementation, and testing procedures is to categorize skin lesion images into classes based on benign, malignant melanoma, acne, eczema, and health. In order to prevent over fitting, the ECOC SVM classifier is employed in conjunction with a 10 fold cross validation technique for classification. It is deduced that the features derived from the convolutional neural network have the potential to improve the classification accuracy of various skin lesions. In [11], an automated technique for classifying skin diseases utilizing Mobile Net V2 and LSTM models is proposed. The research provided insights into the viability and efficacy of integrating complex neural network models for precise disease identification and classification, highlighting the potential of using advanced deep learning architectures in the development of automated skin disease classification systems. In [12], a skin disease module that categorizes lesions related to skin cancer has been suggested. It uses machine learning algorithms to classify skin lesions, such as melanoma and benign keratosis. Using the Keras architecture for training, the skin disease detector uses a Mobile Net convolutional neural network on a Raspberry Pi to classify skin lesions. It is observed that depth wise separable convolution, which TMobileNet CNN implements, utilizes less computational resources than normal convolution. This skin disease detector includes potential features could help doctors diagnose skin diseases more accurately. It also assists users in preaccess so they can receive the early prescriptions needed for appropriate medical care in order to diagnose and treat the illness. A medical expert system based on a Raspberry Pi is suggested in [13] to offer a preliminary diagnostic for patients suspected of having dengue, chikungunya, or malaria, which are diseases spread by mosquitoes. Weighted rules are combined with fuzzy logic to construct the expert system. The system records the user's vital signs and symptoms in a manner similar to a traditional checkup routine. It consists of an electronic blood pressure monitor with built in pulse rate sensor, temperature sensor, and human machine interface. The technology accurately prediagnosed the diseases carried by mosquitoes by comparing its preliminary diagnosis with the expert diagnosis.

III. PROPOSED METHODOLOGY

The proposed work combines deep learning techniques with the automatic classification of different skin disorders. An intelligent and embedded system utilizing a Raspberry Pi is suggested. The system is intended to identify and classify skin images in real time that are taken with an embedded Pi camera and processed by a deep convolutional neural network model. The model includes many layers, including dense, pooling, and convolutional layers, all of which were trained using a dataset collected by the International Skin Imaging Collaboration (ISIC) archive. The model was first developed on a computer and then serialized to a Raspberry Pi for real time execution. It is written in Python using the Keras and tensor flow frameworks. Asymmetry, border irregularity, compact index, fractal dimension, edge abruptness, and colour fluctuation are some of the features of skin images.

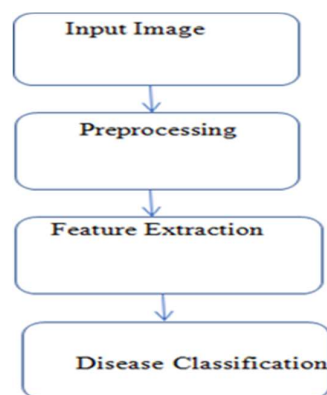


Fig.1. Block diagram of multiclass skin disease classification system

In the proposed automatic skin disease detection systems, image segmentation plays an essential role in extracting and analyzing such information. A support vector machine (SVM) based image segmentation approach is used in this work. Neural network training requires a large and diverse set of dermatoscopic data. A dataset of 3,297 images with a resolution of 600x450 pixels, divided into four groups, is used to train the model. The four categories of skin conditions include eczema, psoriasis, melanoma, and healthy skin. Figure 1 illustrates the main process of the suggested deep learning model prior to serialization in Raspberry pi.

The convolutional neural network algorithm with multiple layers is used in the proposed artificial intelligence model for the detection and classification of skin diseases using dermoscopy images. Activation functions are used in the classification layer to achieve optimal accuracy. The algorithm extracts the maximum of features to improve the accuracy. The suggested model includes a data preprocessing step that involves resizing images, cleaning, transforming, and augmenting data. The CNN method is used to extract features of the lesion. The key objective of data cleaning is reducing the level of noise in the image data set. Nonlocal denoising, wave filters, and hair removal are some of the techniques used to remove noise. The purpose of data conversion is to normalize, convert to grayscale, and change the size of the image collection. The two primary techniques for adjusting size are scaling and clipping. The most widely used data cleaning technique in image preprocessing is to remove noise and hair from the skin disease data set.

In the proposed work, unwanted artifacts like hair are removed from the images using a bottom hat filter with structural characteristics and a Gaussian filter. This approach yields 95% accuracy and is good in comparison to other existing techniques. Image denoising is a method for reducing noise in a noisy image. Real image restoration is made possible by this process. The denoised image loses information when the high frequency components like noise, edge, and texture are examined. The goal of noise reduction is to reduce the image noise while maintaining true features and increasing the signal to noise ratio (SNR). Noise reduction is achieved through the application of spatial filtering in this work with an accuracy rate of more than 95%. In comparison to the current bilateral and Gaussian noise removal filtering methods, it performs better in the prediction of skin diseases.

The Gaussian filter is used to smooth the image and eliminate the noise. It is an effective method for enhancing image quality by removing paper noise and salt from images while keeping the edges intact [14]. A smoothed pixel based on power to power coefficients is called a Gaussian filter. The majority of images of skin diseases contain Gaussian noise. In this work a greater accuracy in MSE and PSNR is obtained by using a Gaussian filters to remove the noise. The smoothing function can be expressed as

$$P_{smooth}(X,Y) = (C_{normalA} + C_{normalB}) \sum_{in}^2 = -2 \sum_{ik}^2 -2 (C_{ijA} + C_{ijB}) P_{row}(X+i,Y+j) \quad (1)$$

where $P_{smooth}(X,Y)$ and $P_{row}(X+i,Y+j)$ denote the smoothed and raw pixel respectively and C_{normal} represent the approximation Gaussian coefficient.

TABLE 1. FILTER PARAMETERS

Type of Filter	MSE	PSNR	Entropy	Type of Noise
Gaussian Filter	18.5	11.9	5.21	Gaussian Noise
	30.2	26.9	5.49	Salt and Pepper Noise
	27.7	25.8	6.48	Speckle Noise

Table 1 shows the result of filter parameters after gaussian filtering. The primary goal of data conversion is to transform the data from one format to the other. The most popular methods for converting data are size adjustment, normalization, and graying. Size adjustment plays an important role in image preprocessing techniques since images with a large size may include insufficient information and require more calculations. As a result, model in the deep learning network include fixed size inputs of 227 * 227. The two basic methods used to change size are scaling and clipping. The dermatological image data set was clipped using the Gamat clipping technique. This technique reduces the calculation time by using a single channel to create grayscale images from the original images. The gray world colour constancy algorithm which is more effective than the current approaches is used for normalizing images of skin diseases [15]. To increase the image brightness and threshold processing, gray conversion techniques are used for each pixel in the image. This work uses a pipeline method for processing grayscale images. It makes use of task specific procedures connected to the classification of skin lesions and promotes improved generalization capabilities. To enhance identification, the textured properties of various skin disorders can be detected to extract the affected area. This allows for the identification of eczema, psoriasis, and melanoma. The watershed technique is used for image segmentation since the majority of skin

conditions take the form of circles. The suggested approach segments the image using a combination of clustering and the marker controlled water segmentation. The diseased area of various skin diseases can be retrieved based on texture identification in order to compute the area of skin diseases under consideration, thereby improving detection and treatment. Each image is divided into relatively small zones such as S_i , $i=1, 2, \dots, W$ in order to segment the image using the watershed method with an appropriate threshold. The locations that have been incorrectly divided must be marked and the feature data of these areas should be initialized into four clusters as the normal skin zone, the skin disease zone, and the incorrectly cut zone. Then determine which of the four clustering forms represents a huge unit, with a lesser number of units contained in each. By estimating the pixel area, various skin diseases can be distinguished from one another. The output of the marker control based clustering segmentation is shown in Fig.2.

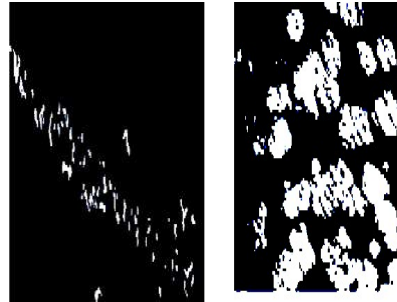


Fig.2. Marker control based clustering segmentation

The support vector machine (SVM) classification method is used which is appropriate for small sample size classification. By examining the provided training set in order to forecast the test set, it can derive the minimal training error as well as a confidence interval term. This work presents the SVM based identification of three distinct skin disorders. The extracted features (such as colour and texture features) are first used to pick the sample and training numbers. Then, the classification model can be created using the support vector machine's rational kernel function. In this paper, three common skin diseases Eczema, Melanoma, and psoriasis are represented as Class I, Class II and Class III, respectively. Integration of texture feature classifier and lesion area feature is used in the image classification. The optimal classification function and the kernel function are defined as

$$f(x) = \text{sgn}\left\{\sum_{j=1}^n a_j y_j k(x_i, y_j) + b\right\} \quad (2)$$

where a_j is a Lagrange multiplier, b is the bias, $k(x_i, y_j)$ is a kernel function. x_i is the Eigen vector that is obtained from the characteristic model and σ is the parameter value in the radial basis function

$$k(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right)$$

IV. SYSTEM DESIGN

The proposed solution couples a Raspberry Pi 3 Model B to a Raspberry Pi NoIR Camera V2, enabling the Raspberry Pi to capture an image of the diseased human skin. The image classifier used in this work must be trained. The training process is performed on a desktop with a powerful CPU and large memory capacity due to the Raspberry Pi's restricted resources. Google created Tensor Flow, an open source software package is used to train the image classifier. The training uses the approach known as transfer learning since it minimizes the amount of complexity and training time. The core of the system is the trained image classifier and the Pi camera, which are both administered by the Raspberry Pi. The image is taken by the Pi camera and saved in a particular file on the Raspberry Pi's storage. The user can access the data from the display module, which shows the most recent classification of the image as either healthy or diseased skin, once the retrained image classifier has classified the image.

There are many functional modules in the system. The image classifier must be trained with the Retrain module. It contains all of the necessary files, including pre trained models to minimize on training time and training scripts, to enable the classifier to be instructed. This module also includes basic operations like changing different pretrained models and fine tuning parameters. The image capture module is responsible for updating the Pi camera's settings, managing the image capture timer, saving the image to a particular file, reporting the

system's status, and automatically restarting the machine in the event of an error. The captured images are categorized by the Label Image module. It finds the path of the stored captured image and loads it. The system incorporates a display device to provide real time feedback and an image representation of the result analysis. An LCD screen that is accessible on a linked monitor serves as the display unit. The diagnostic information is presented with the analyzed images, enabling healthcare providers to promptly recognize the results and make well informed decisions regarding patient care. In addition, the system has two ways for providing images for analysis: directly taking images with the camera module or uploading pictures from external storage devices. When the system software is operating, the Raspberry Pi can operate automatically after the configuration has been set up. The user can see the classification result once the system has finished running. To use the video streaming service, the user can also click on the camera. If the classification result matches one of the skin disorders in the image classifier model, the program displays it. Thus, to provide a complete solution for multiclass skin disease detection using Raspberry Pi technology the suggested system includes power supply, voltage regulation, Raspberry Pi, camera, display and input mechanisms. The prototype of the multiclass skin disease classification system is shown in Figure.3. This proposed work involves a deep learning architecture with various layers that is based on the CNN algorithm. This model is transmitted to the Raspberry Pi following the training procedure to enable real time skin condition diagnosis. The model is implemented on the Tensor Flow framework with open source Keras packages, and it is trained using the google colab platform. The data is divided at random and compiled using a number of hyper parameters for training, including stochastic gradient descent as the optimizer with learning rates of 0.0001, 0.00001, and 64 and 128 batches. An accuracy of 92% is attained after tuning. The core objective is to detect skin diseases in several classes using an embedded system. To accomplish this generated classification model is copied to the Raspberry Pi and serialized. The obtained area under the curve receiver operating characteristics (AUC-ROC) value is 0.912, indicating 91% classification accuracy. It is observed that the suggested approach performs better because it selects an appropriate activation function for the classifier and adopts an efficient feature extraction strategy, resulting in an accurate multiclass skin disease classification.

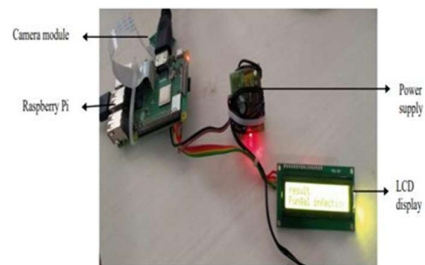


Fig.3. Prototype of the multiclass skin disease detection system

V. CONCLUSION

A prototype of the skin disease detection system is developed in this research work. This system can take images and its image classifier can identify different types of diseases based on whether the image is in a healthy or diseased state. A Raspberry Pi 3 coupled with a Raspberry Pi camera power the entire system. A significant advancement in the realm of medical technology is the use of Raspberry Pi to construct a multiclass skin disease detection system. This solution makes use of the Raspberry Pi's portability and processing capability to provide an affordable and accessible approach to precisely identify a variety of skin disorders. The system can accurately diagnose various skin disorders by combining machine learning algorithms and image processing techniques, which expedites the diagnosis and treatment of skin conditions. Moreover, the compact nature of Raspberry Pi makes it possible to implement this technology in environments with limited resources bringing its advantages to marginalized areas where access to specialized medical care is restricted. The scalability and prospective improvements of the skin disease detection system are made possible by the Raspberry Pi's adaptability. Future scope of this research work can incorporate additional capabilities including patient data management, real time monitoring, and remote consultation with healthcare specialists. In order to enhance the system's diagnostic skills across a variety of demographics and skin types, partnerships with dermatologists and other medical professionals can help further improve the algorithms and build the database. Thus this approach can bring a transformative change in the diagnosis and treatment of skin disorders, leading to better patient outcomes and increased equity in healthcare around the world.

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