Revolutionizing Skin Disease Classification with Machine Learning

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Abstract:

Skin disease is a very common disease for humans. In the medical industry detecting skin disease and recognizing its type is a very challenging task. Due to the complexity of human skin texture and the visual closeness effect of the diseases, sometimes it is really difficult to detect the exact type. The most melanoma type of cancer if not detected in early stages, then it spread to other parts of the body very easily in no time. Therefore, it is necessary to detect and recognize the skin disease at its very first observation. In today's era, the use of artificial intelligence is rapidly growing in medical field. Different machine learning and deep learning algorithms are used for diagnostic purposes. These methods drastically improve the diagnosis and also speed up the process. In this paper the techniques like Convolutional Neural Network and OpenCV picture-handling techniques to recognize and classify various types of skin diseases are implemented. Dermoscopic images are considered as inputs in the pre-handling stages. A system that can analyze images and notify dermatologists of the existence of skin disease might potentially eliminate the need for a lot of manual diagnosis work. The result showed greater accuracy and promising signs that machine-learning algorithms can indeed assist in early identification of the disease and improvement of the treatment outcome.

Keywords: Classification, Convolutional Neural Network, OpenCV image handling, performance measures.

1 Introduction

In the current healthcare industry, the speedy development of technology has become critical for the detection and prognosis of various medical situations. This is mainly authentic for dermatology, in which identification of pores and skin sicknesses is essential for timely intervention and treatment. Although traditional treatment methods are often steeply-priced, time consuming, and sometimes painful, the combination of modern technology has provided a reliable alternative. Previous research on this area has centered on manual testing, which is situation to human mistakes and restrained via medical doctor talent. Although some attempts have been made to use photo processing techniques, the shortage of preferred techniques and the absence of a robust, available devices have avoided their sensible use. most of them focus on the binary classification problem. Often different types of skin pathologies are grouped into the same class and not classified. As an end result, there may be an obvious want for an automatic, reliable, and consumer-friendly system which could correctly diagnose diverse skin diseases at an early degree.

CNNs have gained widespread popularity and proven to be highly effective in various fields, including image recognition, natural language processing, and medical image analysis. Their unique architecture enables them to automatically extract relevant features from raw input data, making them particularly suitable for tasks such as image classification and object detection. In the context of dermatology, CNNs have demonstrated remarkable accuracy in identifying and categorizing various skin diseases based on visual cues and patterns. By processing large datasets of skin images, CNNs can learn to discern subtle differences in textures, colors, and shapes, allowing for the precise classification of different skin conditions by using deep networks for feature extraction and prediction.

The field of dermatology has witnessed remarkable improvements in recent years, especially with the integration of Artificial Intelligence (AI) into classification and diagnosis of various skin diseases. This literature assessment targets to discover the big contributions made with the aid of various researchers in leveraging AI technologies for accurate and green prognosis and remedy of pores and skin diseases.

The study conducted by Keshetti Sreekala et. al. [1] demonstrated the use of Structural Co-occurrence Matrices (SCM) and an advanced Convolutional Neural Network (CNN) in achieving an impressive accuracy rate of 97% in classifying skin diseases. Their approach, incorporating robust preprocessing techniques and advanced deep learning models, significantly improved the quality of image analysis for skin disease classification. J. Samraj and R. Pavithra [2] emphasized the effectiveness of deep learning models, particularly Convolutional Neural Networks (CNNs), in facilitating the accurate and rapid diagnosis of various forms of skin cancer. Their study highlighted the role of image preprocessing techniques and the use of the ISIC 2018 dataset, showcasing the potential of deep learning algorithms like Resnet50, InceptionV3, and Inception Resnet in enhancing diagnostic accuracy, which achieved an overall accuracy rate of 85.7% in the detection of both benign and malignant forms of skin cancer.

Laura Pawlik, et al. [3] focused on the in development occurred in diagnosis and treatment in optimizing the clinical management of melanoma and non-melanoma skin cancer. Their research emphasized on the importance of precise classification and therapy decision-making, portraying importance of the innovative diagnostic techniques available for skin cancer management. Renato Marchiori Bakos et. al. [4] highlighted the significance of noninvasive imaging devices like dermoscopy, Reflectance Confocal Microscopy (RCM), and Optical Coherence Tomography (OCT) in improving the accuracy of skin cancer diagnosis in real-time. Their research emphasized the combination of RCM and OCT as the preferred technique for diagnosing suspicious lesions, enabling effective monitoring of treatment response and adjustments in therapy when necessary.

The work of Karl Thurnhofer-Hemsi et. al. [5] introduced a unique approach that integrated multiple deep-learning classifiers and utilized shifted images to enhance the classification of skin lesions. Their use of deep convolutional classifiers and regular shift patterns showcased the potential of combining the strengths of multiple classifiers to achieve more accurate results. These methods yielded 83.6% accuracy of detection and classification of skin diseases. Fawaz Waselallah Alsaade et. al. [6] demonstrated the effectiveness of a Computer-Aided Diagnosis (CAD) system for the detection of skin cancer, emphasizing feature-based and deep learning approaches using dermoscopy images. Their research highlighted the significant accuracy achieved by the Artificial Neural Network (ANN) model, showcasing the potential of CAD systems in improving the accuracy and efficiency of skin cancer diagnosis.

S. M. Chaware et al. [7], presented an innovative approach to automated skin disease diagnosis. Employing advanced methodologies such as Convolutional Neural Networks (CNN) and image processing algorithms, the system demonstrates high accuracy in recognizing and classifying diverse skin conditions. With its user-friendly interface, real-time diagnostic reports, and personalized recommendations, the proposed system represents a significant step forward in enhancing accessibility and efficiency in remote dermatological care. Kumar Abhishek et. Al. [8] proposed a deep semantic segmentation framework for dermoscopic images that incorporates information extracted using the physics of skin illumination and imaging. Their work focused on addressing challenges related to variations in lesion shape, size, color, and contrast to improve segmentation accuracy. Nawal Soliman et. al. [9] presented an image processing-based approach for detecting skin diseases. The method used a pre-trained CNN (AlexNet), and classification via SVM. Achieving a remarkable 100% accuracy rate, the system successfully identifies three types of skin diseases namely eczema, melanoma, psoriasis. A key emphasis is placed on image resizing for standardization, showcasing the efficiency and simplicity of the proposed system in diagnosing skin conditions, particularly in regions like Saudi Arabia where skin diseases are prevalent due to the hot desert climate.

For skin disease classification various standard datasets are available such as "Human Against Machine with 10000 training images" HAM10000 [10], PH2[11], and various versions of skin disease data archived by International Skin Imaging Collaboration (ISIC)[12, 13]. The archive of skin images is publicly available resource for teaching, research, and the development and testing of diagnostic artificial intelligence algorithms. In [14,15] authors presented challenges in ISIC 2017 and 2018 observed by ISIC in biomedical imaging dataset to improve the algorithm performance and generalize in medical domain.

Overall, the studies have showcased promising levels of accuracy, with a focus on the use of advanced CNNs and deep learning models, highlighting their effectiveness in improving the classification and diagnosis of skin diseases. However, challenges related to variations in lesion characteristics, including shape, size, and color, have posed obstacles to achieve consistent high levels of accuracy. Despite these limitations, the integration of non-invasive diagnostic tools such as optical coherence tomography (OCT) and Reflectance Confocal Microscopy (RCM) has demonstrated potential in enhancing the accuracy of skin cancer diagnosis in real-time, enabling informed treatment decisions.

2 Methodology

The work is divided in three modules Data Preparation, Model Training and Testing shown in fig. 1.1. Three different models are designed and trained. Models refer to the specific configurations of CNN architectures designed to analyze and classify skin lesion images. These models are essentially computational representations of the human decision-making process, built to process input data, extract relevant features, and make accurate predictions regarding the type of skin disease present in the images. Each model is composed of various layers, including convolutional layers, pooling layers, dense layers, and specialized layers such as BatchNormalization and Softmax activation layers.

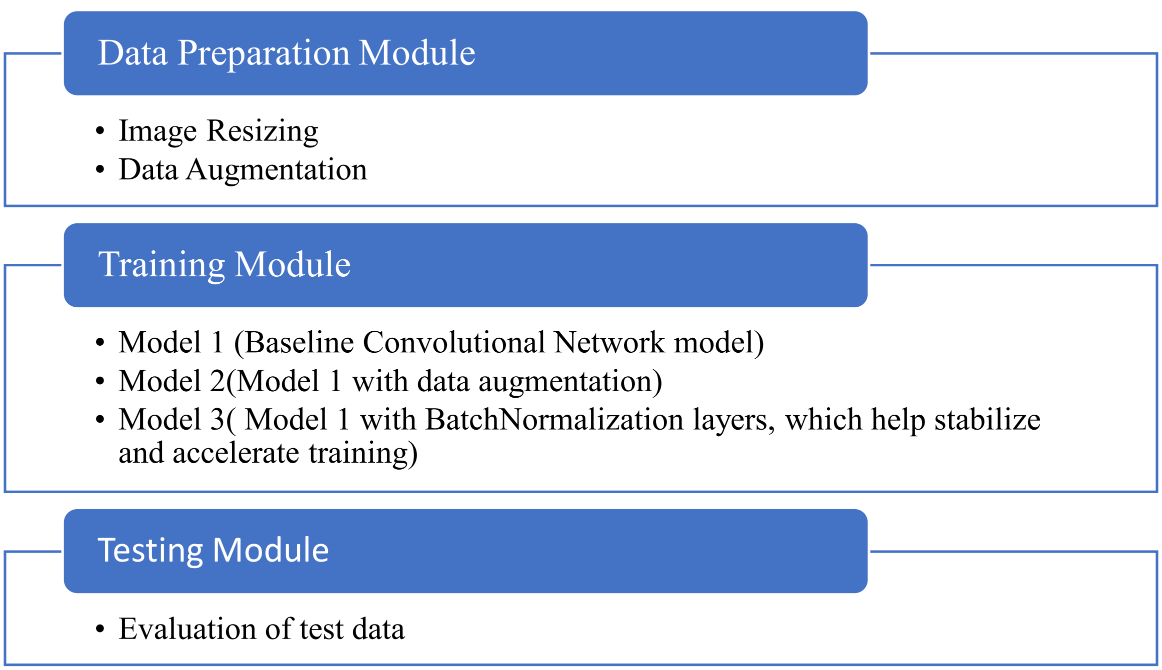

Fig. 1.1 System Design

In Data preparation module, the preprocessing is done on dataset. The skin cancer dataset from the "Skin Cancer (ISIC) 2020 The International Skin Imaging Collaboration."[16] is used for experimentation. It consists of a around

13K collection of images representing nine different classes of skin lesions. The class labels fig. 1.2 shows number of images in testing dataset from each class.

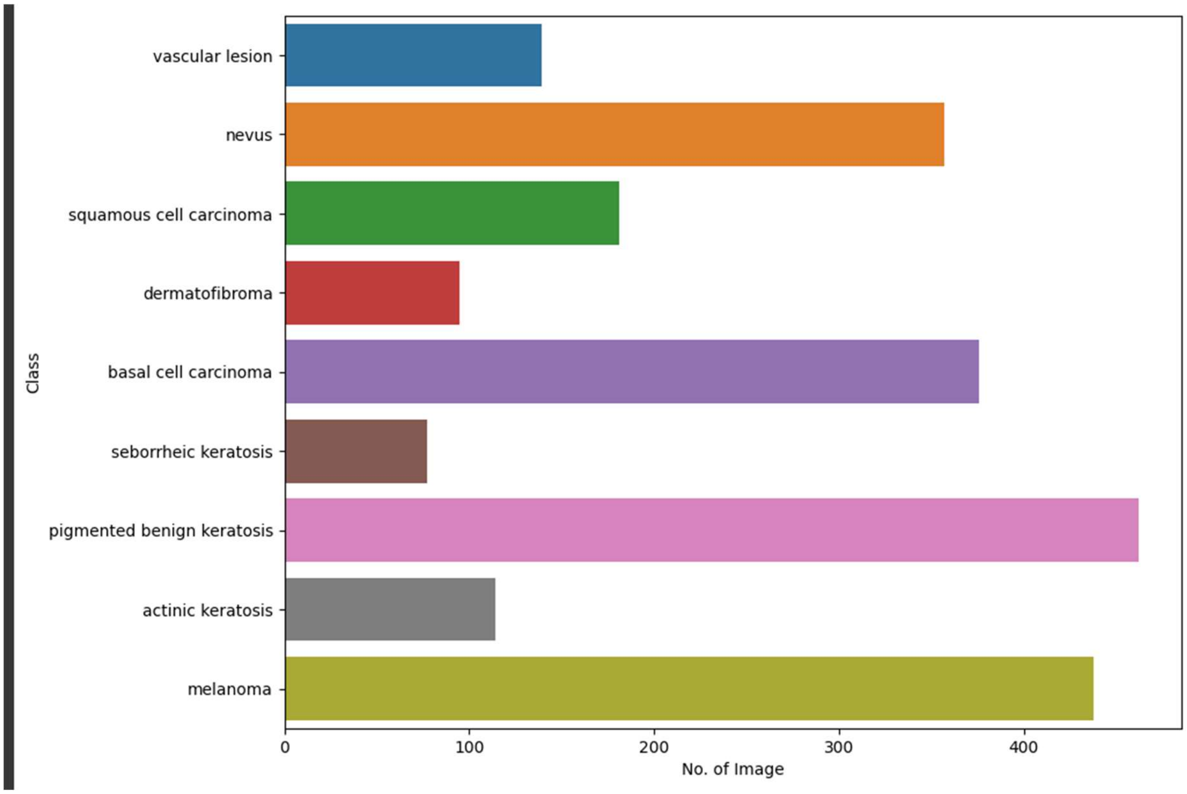

Fig 1.2 No. of samples of testing dataset from each class

The dataset is divided into a 80:20 ratio of training set and testing set. In fig 1.3 few samples from the dataset are shown.

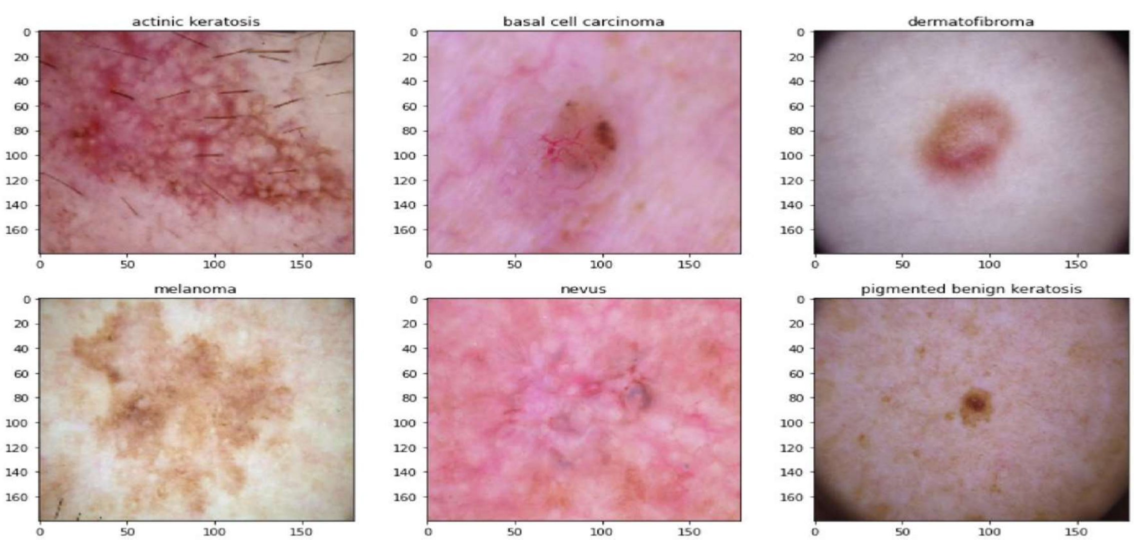

Fig 1.3 samples from the dataset

Data augmentation is done for increasing the diversity of the training dataset, which, in turn, enhances the model's generalization. The following data augmentation techniques were applied to the training images:

- Random horizontal and vertical flipping with a probability of 0.7.
- Random rotations with a maximum left and right rotation of 10 degrees.
- Random zooming with a zoom range of 20%.
- Random translations with horizontal and vertical shifts of 10%.

One sample after augmenting one image is shown in fig. 1.4

Fig 1.4 Augmented sample

The models are trained using the skin cancer dataset, which is prepared by dividing it into a training set and a validation set. During the training process, the models are exposed to the training dataset, and the parameters within the models are optimized using an optimizer. The training involves iterating through the dataset multiple times (epochs), during which the models learn to recognize patterns and features that differentiate different types of skin lesions. The performance of the models is continuously evaluated on the validation dataset, monitoring metrics such as accuracy and loss to assess their ability to accurately classify skin diseases. The training process aims to enhance the generalization and predictive capabilities.

The training is performed using three different models. Model 1 is a baseline convolutional neural network (CNN) architecture, consisting of several convolutional layers, max-pooling layers, and dense layers. It is designed to operate on the original training dataset.
Input shape: (img_height, img_width, 3)
Model 1 Architecture includes:

1 Convolutional Layer 1: 32 filters, kernel size (3, 3), ReLU activation
2 Max-Pooling Layer 1: Pool size (2, 2)
3 Dense Layer: 128 units, ReLU activation
4 Output Layer: len(class_names) units, Softmax activation
5 Training Parameters: Optimizer - Adam, Loss - Categorical Cross-Entropy

Layer (type)	Output Shape	Param #
rescaling (Rescaling)	(None, 180, 180, 3)	0
conv2d (Conv2D)	(None, 178, 178, 32)	896
max_pooling2d (MaxPooling2D)	(None, 89, 89, 32)	0
conv2d_1 (Conv2D)	(None, 87, 87, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 43, 43, 64)	0
conv2d_2 (Conv2D)	(None, 41, 41, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 20, 20, 128)	0
flatten (Flatten)	(None, 51200)	0
dense (Dense)	(None, 512)	26214912
dense_1 (Dense)	(None, 128)	65664
dense_2 (Dense)	(None, 9)	1161

Fig 1.5: Layers used in Model 1 in CNN

Model 2 is an improved version of Model 1, incorporating the augmented dataset. Data augmentation layers were added at the beginning of the model to leverage the augmented images.

1. Input shape: (img_height, img_width, 3)
2. Data Augmentation Layers
3. Model architecture (same as Model 1)
4. Training Parameters (same as Model 1)

Model 3 is another CNN architecture, similar to Model 1, but includes BatchNormalization layers, which help stabilize and accelerate training.

1 Input shape: (img_height, img_width, 3)
2 Rescaling Layer: Scales pixel values to the range [0, 1]
3 Model architecture:
4 Convolutional Layer 1: 32 filters, kernel size (2, 2), ReLU activation
5 BatchNormalization Layer
6 Output Layer: len(class_names) units, Softmax activation
7 Training Parameters: Optimizer - Adam, Loss - Categorical Cross-Entropy

Both the models were trained using the following training parameters:

- Batch Size: 32

- Number of Epochs: 20

The training process involved optimizing the models using the Adam optimizer with categorical cross-entropy loss, and evaluating their performance on the validation dataset. The training and validation accuracy and loss were monitored over epochs.

3. Results & Discussion

The implementation of the skin cancer classification models yielded significant results, showcasing the effectiveness of the developed methodologies. Model 1, serving as the baseline, achieved an impressive accuracy of 89.68% over 20 epochs, demonstrating the capability of the initial CNN architecture to accurately classify various types of skin lesions. However, Model 2, an improved version of Model 1 incorporating the augmented dataset, experienced a slight decrease in accuracy, reaching 62.05% over 20 epochs. This decline could be attributed because of the maximum dropout percentage used. On increasing number epochs upto 50 the accuracy is increased to 89.99%.

The Model 3, enriched with BatchNormalization layers and a rescaling layer, demonstrated the accuracy reaching 91.15% over 50 epochs. The inclusion of BatchNormalization layers contributed to stabilizing and accelerating the training process, resulting in improved model performance. The higher accuracy achieved by Model 2 underscored the importance of incorporating advanced techniques in the model architecture to enhance its ability to accurately classify diverse skin cancer types. Overall, the results highlighted the significance of data augmentation and the utilization of advanced model enhancements, emphasizing the potential of deep learning methodologies in accurate skin cancer classification. Major limitation observed is class imbalance problem. The dataset contains a significant difference in number of samples in every class. Due to this the model may struggle to perform well on the minority class.

4 Conclusion

In summary, the research paper highlights the importance of technological advancements in dermatological diagnosis by utilizing Machine Learning for remote detection of skin diseases. The overall accuracy observed is satisfactory for recognizing various skin conditions through non-invasive techniques like Convolutional Neural Networks and image processing using OpenCV. High accuracy significantly minimizes the risk of misdiagnosis and enables timely interventions, ultimately leading to improved patient care and outcomes. The major limitation observed is class imbalance problem in dataset. As a result, CNNs have become a cornerstone of modern dermatological research and practice, revolutionizing the field and paving the way for more effective and accessible healthcare solutions.

In future, first the focus will be on solving class imbalance problem and then integration of advanced techniques in multispectral imaging technology is planned to incorporate in skin disease classification. The system could capture images at various wavelengths, allowing for the analysis of different skin layers and components such as blood vessels, melanin, and collagen. This would enable a more comprehensive and detailed assessment of skin conditions, potentially enhancing the accuracy of disease identification and providing a deeper understanding of underlying skin pathologies. Furthermore, the incorporation of multispectral imaging could enable the system to detect subtle changes in the skin that might not be visible to the naked eye, thus facilitating the early detection of complex conditions like melanoma and other forms of skin cancer. For this work, only accuracy is used as performance measure in future some other measures also will considered for analysis.

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