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Deep Learning Algorithms for Skin Disease Classification

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Abstract

Skin diseases are a serious concern of public health worldwide, and successful treatment needs a correct and timely diagnosis. Traditional diagnostic methods mostly depend on dermatologist's visual observation and this leads to subjective interpretations coupled with time-consuming processes. Deep learning algorithms have lately been known as powerful means for automated medical image analysis that present more accurate and quicker results at the same time. This study analyses the usage of state-of-the-art deep learning algorithms like YOLOv8, Deep CNN, and ResNet50 used for classification of skin diseases using dermatological images. Classifying the skin conditions relies heavily on the ability to identify and extract essential features. Different skin conditions were covered under large dataset thus providing a comprehensive foundation for training and validation aimed at ensuring that the models could generalize well across different diseases. Each algorithm also employs transfer learning techniques by utilizing pre-trained models based on large image datasets in order to improve adaptability and generalization over new data types. The use of deep learning algorithms in classifying skin diseases represents a significant method to achieve efficient and accurate diagnosis with benefits to both patients and healthcare professionals as is the trend in medical image analysis. The advanced deep learning models introduced in this paper excel at classifying complex skin diseases, outperforming the machine learning approaches in performance.

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1. Introduction

Deep learning algorithms have brought about a revolutionary change in the field of medical image analysis. Deep learning algorithms, fuelled by neural networks, have demonstrated remarkable capabilities in recognizing complex patterns and features within large datasets. The application of deep learning to dermatology holds the promise of enhancing diagnostic accuracy, accessibility, and efficiency. The motivation behind this research is rooted in the imperative for improved diagnostic tools in dermatology. The existing challenges in skin disease diagnosis, including variability in human assessment and the need for swift interventions, underscore the urgency of exploring advanced technologies. It extends to the potential impact on patient outcomes, where quicker and more accurate diagnoses can lead to timely interventions and improved treatment efficacy. Additionally, there is a broader motivation to democratize access to reliable diagnostic tools, particularly in regions where access to dermatological expertise is limited. By harnessing the capabilities of deep learning algorithms, this research seeks to contribute to the development of solutions that transcend traditional constraints in skin disease diagnosis.

2. Related Work

The referenced articles exhibit several limitations in their approaches to skin lesion classification, hindering their comprehensive applicability. Authors in [1] exclusively train and classify skin lesions as benign or malignant using only Melanoma data, potentially limiting its generalization to a broader spectrum of skin diseases. Authors in [2] falls short by solely measuring performance through accuracy, neglecting the inclusion of other crucial metrics that offer a more refined evaluation of the model's effectiveness. Moreover, the authors in [3] fails to specify the predicted diseases, restricting its clinical utility. In contrast, the authors in [4] employs a binary cross-entropy loss function due to a dataset with only two classes, potentially overlooking nuances inherent in multi-class scenarios. Lastly, the authors in [5] dismiss Artificial Neural Networks (ANN) as less potent than Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) without considering the specific task at hand.

To overcome these limitations, the proposed system embraces a holistic approach. Three different deep learning algorithms—YOLOv8, Deep-CNN, and ResNet50 are introduced—to enhance the versatility and effectiveness of the skin lesion classification. By incorporating diverse algorithms and classifying three distinct skin diseases—acne, bcc, and melanoma—the shortcomings of prior studies are addressed and a a more comprehensive, clinically relevant solution is provided. This multi-algorithmic approach, coupled with a diverse dataset and a range of performance metrics, ensures a robust and adaptable skin lesion classification system with broader applicability in clinical settings.

3. Proposed Work

This study focuses on the application and comparative analysis of three deep learning algorithms – YOLOv8, Deep CNN, and ResNet50 – for skin disease classification. Each algorithm is explored independently, considering its unique architecture and strengths. Pre-processing techniques, feature extraction, and model architecture selection will be crucial components in achieving robust performance. The concentration areas include optimizing parameters for efficient detection and classification, utilizing transfer learning techniques to enhance adaptability, and evaluating the performance of each algorithm against established metrics such as accuracy, precision, recall, and confusion matrix. By concentrating on these aspects, we aim to unravel the nuanced capabilities of these algorithms in the context of dermatological diagnostics, providing valuable insights for future advancements in automated skin disease classification.

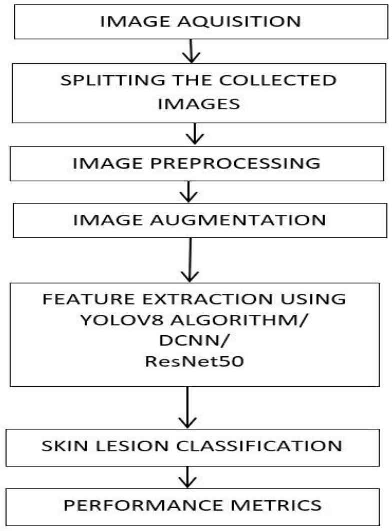

Figure 1. Proposed System Flow Diagram

3.1. Image Acquisition

The initial step in our system involves collecting diverse and representative skin disease images. For basal cell carcinoma (BCC) and melanoma, we have leveraged from the HAM10000 dataset, a comprehensive collection of dermatoscopic images. The images for acne have been sourced from the Kaggle dataset dedicated to acne-related skin conditions. This dataset selection ensures a well-rounded representation of various skin diseases, offering a rich and diverse set of images for training and testing our models.

3.2. Splitting the Collected Images

Organizing the collected images into distinct categories is imperative for effective training and evaluation. Python code is employed to categorize images based on their associated skin diseases. This categorization ensures that each algorithm receives a well-organized and disease-specific dataset during training. The dataset used in this study consists of images representing three types of skin diseases: acne, basal cell carcinoma (BCC), and melanoma (mel). The number of samples collected for each type of skin disease and the distribution per class within each disease category are as follows:

Acne

Total Samples: 400

Training Set: 280 samples

Validation Set: 80 samples

Test Set: 40 samples

Basal Cell Carcinoma (BCC)

Total Samples: 400

Training Set: 280 samples

Validation Set: 80 samples

Test Set: 40 samples

Melanoma (Mel)

Total Samples: 400

Training Set: 280 samples

Validation Set: 80 samples

Test Set: 40 samples

These samples were split into training, validation, and test sets with proportions of 70%, 20%, and 10%, respectively, for each class within each skin disease category.

3.3. Image Pre-processing

Once the images are acquired, the next crucial step is pre-processing, where we employ OpenCV for a myriad of image enhancement techniques. This includes resizing images to a standard size, normalizing pixel values to ensure consistent intensity across the dataset. Furthermore, noise reduction and contrast adjustments are implemented to enhance the quality of images, preparing them for the subsequent stages of our pipeline.

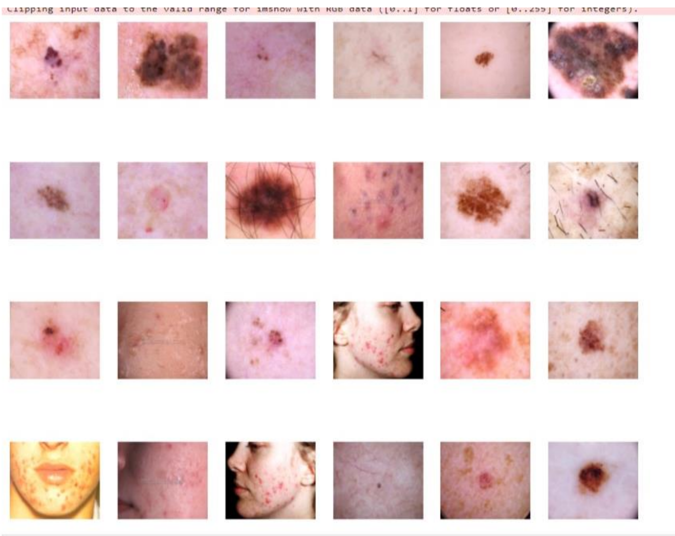

Figure 2. Output after Image Pre-processing

The OpenCV method cv2.resize() is used for resizing the image and cv2.cvtColor() method is used for converting the images from BGR to RGB color format. Further, for normalization, each pixel value in an image is divided by 255 to normalize from 0 to 1. Gaussian blur is applied to images using the cv2.GaussianBlur() method with a kernel size of (5, 5). This helps reduce noise and smooth images. Contrast is increased by multiplying the image by 1.2.

3.4. Image Augmentation

Image augmentation is a technique widely used in computer vision to increase the diversity of training data without collecting new samples. The method involves applying various transformations to the original images, thereby creating new instances while preserving their semantic content. The random rotation is used, which helps the model become invariant to different orientations. The images are randomly zoomed, enhancing its robustness to scale variations. Horizontal flipping introduces mirror images, aiding the model to generalize better. These techniques simulate real-world scenarios and contribute to the model's ability to learn invariant features.

3.5. Feature Extraction using Deep Learning Algorithms: YOLOv8, Deep CNN, and ResNet50

This module involves the implementation of three state-of-the-art deep learning algorithms for feature extraction. Each algorithm is applied independently to the categorized dataset, extracting intricate features relevant to skin disease classification.

3.5.1 YOLOv8

YOLOv8 excels in real-time object detection and is particularly suited for skin lesion identification. The algorithm's grid-based approach facilitates efficient localization of lesions, and the bounding box predictions, along with class probabilities, are crucial features extracted during this phase.

YOLOv8-cls is an image classification model, part of the YOLOv8 family of models from Ultralytics. It is done by classifying the entire image into one of the predefined class groups. The YOLOv8 series provides a variety of examples for different tasks, including detection, segmentation, and classification. The YOLOv8-CLS model is previously trained on the ImageNet dataset and yields a range of different accuracies and speeds. The design of the model has a backbone and a head, the head incorporates a focusing mechanism, so that the model focuses on different parts of the image YOLOv8-CLS is customizable larger, provides pre-trained models, supports adaptive training and data advanced techniques.

3.5.2 Deep CNN

Our customized Deep CNN architecture is designed to capture hierarchical features specific to dermatological images. Convolutional layers play a pivotal role in extracting textures and patterns indicative of various skin diseases, contributing to discriminative feature extraction.

3.5.3 ResNet50

Leveraging ResNet50 addresses the challenge of training deep networks. The skip connections in ResNet50 aid in preserving detailed information during feature extraction, allowing the model to capture intricate features relevant to skin disease classification.

3.6. Skin Lesion Classification

After feature extraction, each algorithm is trained on the skin lesion dataset. The training process involves optimizing model parameters using backpropagation and gradient descent. Once trained, the models are capable of classifying skin lesions into predefined categories: acne, BCC, or melanoma. The classification results are then evaluated on a separate testing dataset to assess the models' accuracy and generalization capabilities.

3.7. Performance Metrics

The selection of performance metrics is a critical aspect in evaluating the efficacy of skin disease classification systems. This choice is contingent upon the specific objectives of the application and the inherent characteristics of the problem at hand. In the realm of skin disease classification, the metrics of accuracy, precision, recall, and the confusion matrix are strategically chosen for their distinct roles in assessing the model's performance.

The combination of accuracy, precision, recall, and the confusion matrix offer a comprehensive evaluation of the model's performance. It ensures a balanced assessment of the classification system from different perspectives. Each metric addresses a specific aspect of model performance, contributing to the system's robustness and reliability in real-world dermatological diagnostics.

4. Results and Discussion

The skin disease classification models are implemented in Python language, through Anaconda Jupyter Notebook which served as the primary programming environment. Several libraries and tools were utilized for different tasks, including pre-processing, model building, and evaluation. For pre-processing tasks such as image loading, resizing, OpenCV (Open Source Computer Vision Library) was employed [6]. ImageDataGenerator, a part of Keras, was used for data augmentation during model training, enhancing the model's ability to generalize.

The models were implemented using TensorFlow and Keras [7], two widely-used deep learning frameworks. The 'Model' class from Keras is used for the creation of arbitrary layer graphs, making it suitable for building more complex models with multiple inputs or outputs. The 'Sequential' class from Keras is used for the creation of sequential neural network models where layers are stacked sequentially. The layers from Keras such as GlobalAveragePooling2D, MaxPooling2D, Conv2D, Dense, Dropout, and Flatten are used. The Adam optimizer, a variant of stochastic gradient descent, was employed for optimizing the model parameters during training. It adapts the learning rate for each parameter based on the past gradients, making it suitable for training deep neural networks.

The scikit-learn (sklearn) library was utilized for evaluating the model's performance, specifically for generating classification reports and confusion matrices [8]. It provides comprehensive tools for machine learning tasks, including evaluation metrics for classification tasks. NumPy was used for numerical computations and array manipulation [9]. It provided efficient data structures and operations for handling the input data and model parameters. Matplotlib library is used for plotting for Python [10]. Three different algorithms were employed: YOLOv8, Deep Convolutional Neural Network (DCNN), and ResNet50 for skin lesion classification.

Table 1. Performance Metrics

ALGORITHM	RECALL	PRECISION
YOLOv8	84.81	85.33
DCNN	86.67	86.67
ResNet50	83	84

Table 2. Features Identification

FEATURES	YOLOv8	DCNN	ResNet50
Grid-based Detection	YES	NO	NO
Bounding Box Prediction	YES	NO	NO
Real-time Detection	YES	NO	NO
Hierarchical Features	NO	YES	YES
Convolutional Layers	NO	YES	YES
Skip Connections	NO	NO	YES
Transfer Learning	YES	YES	YES
Multi-class Classification	YES	YES	YES
Efficient Parameter Optimization	YES	YES	YES

Table.1 shows the performance measured by recall and precision of the three algorithms. DCNN achieved the highest recall (86.67%) and precision (86.67%) values, indicating strong performance in correctly identifying positive cases and minimizing false positives. YOLOv8 and ResNet50 exhibited competitive recall and precision values, with YOLOv8 having slightly lower precision than DCNN.

Table.2 shows the features identified in each algorithm. Feature identification plays a pivotal role in improving skin disease classification by enabling the extraction of relevant information from skin lesion images. Techniques such as grid-based detection and bounding box prediction, supported by YOLO-v8 algorithm, provide valuable insights into the localization of lesions within the image, thus aiding in the identification of specific regions of interest. This localized information is crucial for accurate classification. Additionally, hierarchical feature extraction, convolutional layers, skip connections, and transfer learning, employed by various algorithms, contribute significantly to enhancing classification accuracy. Hierarchical features allow the model to capture intricate details about skin lesions, while convolutional layers extract discriminative features from the images. Skip connections alleviate the vanishing gradient problem, leading to more accurate results. Transfer learning leverages pre-trained models to extract generic image recognition capabilities, which are then fine-tuned for the specific task of skin disease classification, improving both efficiency and accuracy. Multi-class classification further enables the model to differentiate between various skin diseases based on the extracted features, facilitating comprehensive diagnosis. Therefore, robust feature identification techniques are essential for accurate and efficient skin disease classification, providing valuable insights for medical practitioners in diagnosing and treating patients.

5. Conclusion

In our proposed system, we have introduced a comprehensive approach to skin disease classification using three distinct deep learning algorithms: YOLOv8, Deep CNN, and ResNet50. The primary goal is to leverage the strengths of each algorithm to create a robust and adaptable skin lesion classification system. The models were evaluated based on key performance metrics, including recall and precision. DCNN achieved the highest values for both metrics, showcasing its ability to correctly identify positive cases while minimizing false positives. While the proposed system lays a strong foundation for automated skin disease classification, there are several avenues for future work and improvements such as Data Expansion, User Interface deployment etc.

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