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Deep Learning Based Skin Disease Detection

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Abstract

Skin diseases affect millions of people worldwide and require accurate diagnosis for effective treatment. Traditional diagnostic methods often depend on expert dermatologists and manual examination, which may lead to delays and errors. This proposed system introduces a Genetic Algorithm Optimized Stacking Approach for Skin Disease Detection using deep learning techniques. The system combines multiple models including ResNet50, DenseNet121, and CNN through an ensemble stacking framework optimized by a Genetic Algorithm. Image preprocessing techniques such as resizing, normalization, and augmentation improve data quality and model performance. The proposed model is trained on the DermNet dataset containing more than 19,000 images across 23 skin disease classes. Experimental results demonstrate improved classification accuracy and Top-5 accuracy compared to individual models. The system provides an efficient and reliable solution for automated skin disease diagnosis and supports healthcare professionals in decision-making.

Keywords Skin Disease Detection, Deep Learning, Genetic Algorithm, Ensemble Learning

Introduction

Skin diseases are among the most common medical conditions affecting people worldwide and can significantly impact an individual's physical health, psychological well-being, and quality of life. These diseases include a wide range of conditions such as eczema, psoriasis, acne, melanoma, fungal infections, and bacterial infections. According to global health reports, skin diseases contribute substantially to disability-adjusted life years (DALYs) and remain a major public health concern. Early and accurate diagnosis is essential because delayed detection may lead to severe complications, increased treatment costs, and reduced effectiveness of medical interventions. However, the growing number of skin diseases and their similar visual appearances make diagnosis a challenging task even for experienced dermatologists.

Traditionally, skin disease diagnosis relies on clinical examination, laboratory testing, and expert interpretation of skin lesions. While these methods are effective, they are often time-consuming, expensive, and dependent on the availability of specialized healthcare professionals. In many rural and underserved regions, access to dermatologists is limited, resulting in delayed diagnosis and treatment. Moreover, human diagnosis may be influenced by factors such as fatigue, experience level, and subjective interpretation, potentially leading to diagnostic errors. Therefore, there is a growing need for automated and intelligent diagnostic systems that can assist healthcare professionals and improve the accessibility of skin disease screening.

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have revolutionized the field of medical image analysis. Deep learning models, particularly Convolutional Neural

Networks (CNNs), have demonstrated remarkable success in image classification, object detection, and disease diagnosis tasks. These models automatically learn complex visual patterns from large datasets and can identify subtle features that may not be easily observable by humans. In dermatology, deep learning-based systems have shown significant potential in detecting and classifying skin diseases using dermoscopic and clinical images, thereby enhancing diagnostic accuracy and supporting clinical decision-making.

Despite these advancements, existing skin disease detection systems still face several limitations. Many studies are trained on small datasets containing a limited number of disease categories, which reduces their ability to generalize to real-world scenarios. Additionally, environmental variations such as lighting conditions, camera quality, image resolution, and skin tone differences can adversely affect model performance. Individual deep learning models may also suffer from overfitting or insufficient learning capacity when dealing with highly diverse skin disease datasets. These challenges highlight the necessity for more robust and adaptive classification approaches capable of handling large-scale and heterogeneous medical image data.

To address these limitations, this research proposes a Genetic Algorithm Optimized Stacking Approach for Skin Disease Detection. The proposed system combines the strengths of multiple deep learning architectures, including CNN, ResNet50, and DenseNet121, through an ensemble learning framework. A Genetic Algorithm is employed to identify the most effective combination of models and optimize the ensemble structure. By leveraging advanced image preprocessing techniques, deep feature extraction, and evolutionary optimization, the proposed approach aims to achieve superior classification accuracy and improved generalization. The system is trained and evaluated using the DermNet dataset containing over 19,000 images across 23 skin disease categories. Experimental results demonstrate that the optimized ensemble model outperforms individual classifiers and provides a reliable solution for automated skin disease diagnosis, thereby supporting healthcare professionals in making faster and more accurate clinical decisions.

Related Work

Atlanta [1], Get an overview of melanoma skin cancer and the latest key statistics in the US. Melanoma accounts for only about 1% of skin cancers but causes a large majority of skin cancer deaths. If you have been diagnosed with melanoma skin cancer or are worried about it, you likely have a lot of questions. Learning some basics is a good place to start.

MUHAMMADUMAR [2], In this paper, an explainable artificial intelligence (XAI) based skin lesion classification system is proposed to improve the skin lesion classification accuracy. This will help the dermatologists to make rational diagnosis in the early stages of skin cancer. The proposed XAI model is validated using International Skin Imaging Collaboration (ISIC) 2019 dataset. The developed model correctly identifies the eight types of skin lesions (dermatofibroma, squamous cell carcinoma, benign keratosis, melanocytic nevus, vascular lesion, actinic keratosis, basal cell carcinoma and melanoma) with classification accuracy, precision, recall and F1 score as 94.47%, 93.57%, 94.01%, and 94.45% respectively.

Rebecca L. Siegel [3], Colorectal cancer (CRC) is the second most common cause of cancer death in the United States. Every 3 years, the American Cancer Society provides an update of CRC occurrence based on incidence data (available through 2016) from population-based cancer registries and mortality data (through 2017) from the National Center for Health Statistics. In 2020, approximately 147,950 individuals will be diagnosed with CRC and 53,200 will die from the disease, including 17,930 cases and 3,640 deaths in individuals aged younger than 50 years.

Mohammed Rakeibul Hasan [4], is research contains information about many CNN models and a comparison of their working processes for finding the best results. Pretrained models like VGG16, Support Vector Machine (SVM), ResNet50, and self-built models (sequential) are used to analyze the process of CNN models. ese models work differently as there are variations in their layer numbers. Depending on their layers and work processes, some models work better than others. An image dataset of benign and malignant data has been taken from Kaggle. In this dataset, there are 6594 images of benign and malignant skin cancer. Using different approaches, we have gained accurate results for VGG16 (93.18%), SVM (83.48%), ResNet50 (84.39%), Sequential_Model_1 (74.24%), Sequential_Model_2 (77.00%), and Sequential_Model_3 (84.09%).

Walaa Gouda [5], In this research, the deep learning method convolution neural network (CNN)was used to detect the two primary types of tumors, malignant and benign, using the ISIC2018 dataset. This dataset comprises 3533 skin lesions, including benign, malignant, non -melanocytic, and melanocytic tumors. Using ESRGAN, the photos were first retouched and improved. The photos were augmented, normalized, and resized during the preprocessing step.

Md. Al-MamunProvath [6], Cyclic learning rate is employed to increase the accuracy and maintain the computational efficiency of the proposed methods. This is both straightforward and effective which facilitates the model to con verge faster. Several transfer learning models that have already been trained are also used, and they are compared to the proposed CNN from scratch. It is found that the proposed model provides better accuracy, reducing the impact of inter-class variations between Lung Adenocarcinoma and another class Lung Squamous Cell Carcinoma. Implementing the proposed method increased total accuracy to 97% and demonstrate computing efficiency in compare to other method.

Sunday AdeolaAjagbe [7], This study was aimed at advancing AD image classification with deep convolutional neural network (DCNN) involving convolutional neural network (CNN) and transfer learning (Visual Geometry Group (VGG)16 and VGG19) using magnetic resonance images (MRI) and extend the evaluation metrics since limitations and capacity of algorithms cannot be revealed by few metrics. The objectives of this research are to classify AD images into four known classes by neurologists and results of the finding are subjected to many evaluation metrics. This research used computer algorithms majorly DCNN and transfer learning to classify AD. Six metrics were used for the evaluation; accuracy, area under curve (AUC), F1- score, precision, recall and computational time.

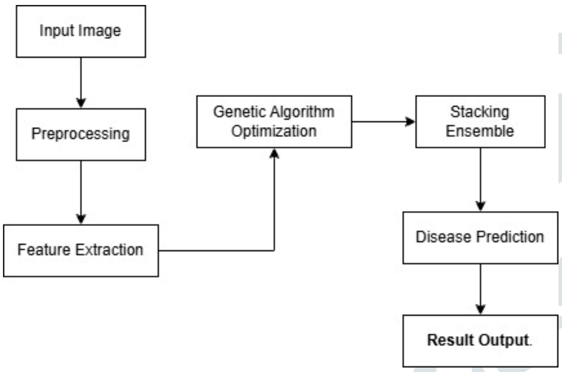
Fawad Ahmed [8], In this paper, the pre-trained MobileNetV2 and DenseNet201 deep learning models are modified by adding additional convolution layers to effectively detect skin cancer. Specifically, for both models, the modification includes stacking three convolutional layers at the end of both the models. A thorough comparison proves that the modified models show their superiority over the original pre-trained MobileNetV2 and DenseNet201 models. The proposed method can detect both benign and malignant classes. The results indicate that the proposed Modified DenseNet201 model achieves 95.50% accuracy and state of-the-art performance when compared with other techniques present in the literature. In addition, the sensitivity and specificity of the Modified DenseNet201 model are 93.96% and 97.03%, respectively.

Advantages

- High skin disease classification accuracy.
- Supports detection of multiple skin diseases.
- Uses large-scale DermNet dataset.
- Reduces diagnostic errors.
- Improves early disease detection.

- Handles variations in skin texture and lighting.
- Genetic Algorithm optimizes model selection.
- Ensemble learning improves prediction reliability.
- Reduces overfitting compared to individual models.
- Can assist dermatologists in clinical decision-making.

System Arrchitecture



1. Input Image

The process begins when a user uploads or captures an image of the affected skin area. The image may contain symptoms of various skin diseases such as eczema, psoriasis, acne, melanoma, fungal infections, or other dermatological conditions. This image serves as the primary input for the detection system.

2. Preprocessing

The uploaded image undergoes preprocessing to improve its quality and prepare it for analysis. This stage includes image resizing, normalization, noise removal, contrast enhancement, and image correction. Preprocessing ensures that all images have a uniform format and quality, which helps improve model performance and reduces classification errors.

3. Feature Extraction

After preprocessing, important visual features are extracted from the skin image using deep learning models such as CNN, ResNet50, and DenseNet121. These models automatically identify significant characteristics including color variations, texture patterns, lesion boundaries, and disease-specific features. Feature extraction converts the image into meaningful numerical representations that can be used for classification.

4. Genetic Algorithm Optimization

The Genetic Algorithm (GA) is used to identify the best combination of deep learning models for the ensemble system. Each model combination is treated as a chromosome, and its performance is evaluated using classification accuracy. Through selection, crossover, and mutation operations, GA searches for the most optimal ensemble configuration that produces the highest prediction accuracy.

5. Stacking Ensemble

The optimized models selected by the Genetic Algorithm are combined using a stacking ensemble technique. Instead of relying on a single model, multiple models work together to make predictions. The outputs generated by CNN, ResNet50, and DenseNet121 are passed to a meta-classifier (dense neural network), which learns how to combine these predictions effectively and produce a more accurate final decision.

6. Disease Prediction

The stacked ensemble model analyzes the extracted features and predicts the most probable skin disease category. The model calculates confidence scores for all disease classes and selects the disease with the highest probability as the final prediction. This step ensures accurate classification even when diseases have similar visual appearances.

7. Result Output

Finally, the system displays the predicted skin disease along with its confidence score. The output can assist dermatologists and healthcare professionals in making diagnostic decisions. The result may also provide the top predicted diseases, helping doctors perform further clinical evaluation and treatment planning.

Proposed System

The proposed system consists of three major modules: preprocessing, prediction, and prediction aggregation. The preprocessing module performs image resizing, normalization, and correction techniques to ensure consistency across all images. Proper preprocessing enhances feature extraction and improves overall classification performance.

The prediction module utilizes multiple deep learning architectures including ResNet50, DenseNet121, and a basic CNN. Each model independently learns discriminative features from skin disease images. These models are trained using the DermNet dataset and evaluated based on performance metrics such as accuracy and loss.

To achieve optimal performance, a Genetic Algorithm is applied to identify the most effective combination of models. The selected models are integrated using a stacking ensemble strategy where predictions from individual models are combined through a dense neural network to generate the final disease classification result. This approach significantly improves accuracy and robustness.

Algorithms

Genetic Algorithm Optimized Stacking Ensemble

The Genetic Algorithm (GA) is an evolutionary optimization technique inspired by natural selection. In the proposed system, GA is used to identify the best combination of deep learning models for ensemble learning. Each ensemble configuration is treated as a chromosome, and its fitness is evaluated using classification accuracy. Ensembles with higher fitness values are selected for crossover and mutation operations to generate improved model combinations.

The optimization process continues for 100 iterations until the best-performing ensemble is obtained. The selected models are then integrated using a stacking framework. Predictions generated by individual models are passed to a dense neural network that learns how to combine them effectively. This results in higher classification accuracy and better generalization compared to individual models.

Dataset Used

Dataset Name: DermNet Dataset

The DermNet dataset is a comprehensive collection of skin disease images used for training and testing the proposed model. It contains more than 19,000 images categorized into 23 distinct skin disease classes. The diversity of diseases included in the dataset enables the development of a robust classification system.

The dataset includes diseases such as Acne, Rosacea, Eczema, Psoriasis, Melanoma, Cellulitis, Lupus, Alopecia, Fungal Infections, Viral Infections, and several other dermatological conditions. The availability of multiple disease categories improves the model's ability to generalize across various skin disorders.

For training and evaluation, the dataset is divided into training and testing sets using an 80:20 split ratio. Images undergo preprocessing and augmentation before being supplied to deep learning models. The large-scale nature of the dataset helps reduce overfitting and enhances classification performance.

Result

1. Experimental Setup

The experimental setup was implemented using TensorFlow for deep learning model development and OpenCV for image processing and augmentation. These frameworks enabled efficient training and evaluation of various neural network architectures.

The models were trained on the DermNet dataset using standard hyperparameters. Various configurations including batch size, optimizers, and loss functions were evaluated before selecting the optimal settings. An 80% training and 20% testing split was used throughout experimentation.

2. Results

Individual deep learning models such as CNN, DenseNet121, ResNet50V2, MobileNet, and EfficientNetV2 were evaluated. While some models achieved high training accuracy, several suffered from overfitting and lower validation performance.

The Genetic Algorithm optimized stacking ensemble achieved the best performance among all tested models. The ensemble demonstrated approximately 85% training and validation accuracy with improved loss characteristics. The proposed system achieved a Top-5 accuracy of 74% on DermNet and 91.73% accuracy on HAM10000.

3. Analysis

The results indicate that ensemble learning significantly improves classification performance compared to individual deep learning models. Combining multiple models enables the system to capture diverse feature representations and reduce prediction errors.

The Genetic Algorithm effectively selected the best model combinations from a large search space. The optimized ensemble demonstrated superior generalization capability and achieved higher accuracy than previously reported methods, making it suitable for real-world skin disease diagnosis applications.

Conclusion

Skin disease diagnosis requires highly accurate and reliable classification systems due to its critical impact on patient health. The proposed Genetic Algorithm Optimized Stacking Approach successfully combines multiple deep learning models to improve classification performance. By integrating CNN, DenseNet121, and ResNet-based architectures within an optimized ensemble framework, the system achieves superior accuracy and robustness. Experimental evaluation on the DermNet and HAM10000 datasets demonstrates significant improvements over existing approaches, achieving a Top-5 accuracy of 74% and classification accuracy of 91.73%. The proposed system provides an effective solution for automated skin disease detection and has the potential to assist healthcare professionals in making faster and more accurate diagnostic decisions.

Declarations

I hereby declare that the project entitled **"Skin Disease Detection Using Genetic Algorithm Optimized Stacking Approach"** is an original work carried out by me under the guidance of my project guide. The information, data, and results presented in this project have been collected from genuine sources and are presented solely for academic purposes. I further declare that this work has not been submitted to any other institution or university for the award of any degree, diploma, or certification.

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