International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Skin Disease Prediction using Neural Networks with Remedy Recommendation

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ABSTRACT:

Skin diseases are a major health problem. Early detection and treatment are essential for preventing complications. Skin disease prediction systems use algorithm to analyze data with skin diseases of patient's medical history, physical examination findings, and laboratory results. The algorithm trained to identify patterns in this data that are associated with different types of skin diseases. These systems can help patients to diagnose skin diseases more accurately and efficiently, and to recommend the most effective treatment. Remedy recommendation systems use algorithms to analyze data, the treatment that they received are trained to identify patterns in this data that are associated with successful treatment outcomes. Once the algorithms are trained, they can be used to recommend the most effective treatment for a new patient, based on data. ARL-CNNs, and Collaborative filtering can be used together to develop powerful and accurate systems for image processing and remedy recommendation. CNNs can be used to extract features from images, ARL-CNNs can be used to train a model to classify the images or detect objects in images and Collaborative filtering can be used to recommend treatments based on the classification results. Skin disease prediction and remedy recommendation systems have the potential to improve the quality with skin diseases receive. By helping patients to diagnose skin diseases more accurately and efficiently, and to recommend the most effective treatment for each patient can helps to improve patient outcomes and reduce the cost of healthcare.

Keywords: Deep learning, image recognition, skin disease, remedy recommendation.

Introduction:

Skin diseases represent a significant health challenge worldwide, affecting individuals of all ages and demographics. Timely detection and appropriate treatment are pivotal in mitigating complications and enhancing patient well-being. In recent years, the integration of advanced algorithms and data analytics has emerged as a promising avenue for improving the diagnosis and management of skin conditions. Skin disease prediction systems harness the power of algorithmic analysis by synthesizing vast arrays of patient data, including medical histories, physical examination findings, and laboratory results. These systems are designed to discern intricate patterns within the data, facilitating the accurate identification of various skin ailments. By leveraging algorithmic insights, healthcare practitioners can streamline the diagnostic process, leading to more precise and efficient treatment recommendations. Furthermore, remedy recommendation systems utilize sophisticated algorithms to scrutinize treatment outcomes and patient responses. By analyzing diverse datasets encompassing treatment modalities and their corresponding efficacies, these systems identify patterns associated with successful therapeutic interventions. Consequently, they empower healthcare providers to make informed decisions regarding the most effective course of treatment for individual patients. The amalgamation of Attention Residual learning convolutional neural networks (ARL-CNNs) and Collaborative Filtering techniques holds immense potential in enhancing image processing capabilities and refining remedy recommendations. Convolutional Neural Networks (CNNs) play a pivotal role in feature extraction from medical images, while ARL- CNNs facilitate robust classification and object detection within these images. Collaborative Filtering algorithms further enrich the process by recommending tailored treatment options based on the classification outcomes, thereby optimizing patient care pathways. The advent of skin disease prediction and remedy recommendation systems heralds a transformative era in dermatological healthcare delivery. By enhancing the accuracy and efficiency of skin disease diagnosis and treatment recommendation, these systems promise to elevate patient outcomes while concurrently mitigating healthcare costs. As such, a comprehensive understanding of the underlying algorithms and their synergistic applications is essential for realizing the full potential of these innovative technologies.

Literature Survey:

[1] ''Classification of the clinical images for benign and malignant cutaneous tumors using a deep learning algorithm,'' J. Investigative Dermatol., vol. 138, no. 7, pp. 1529–1538, Jul. 2018, Doi: 10.1016/j.jid.2018.01.028.. Through rigorous evaluation, the deep learning model demonstrates promising results in accurately distinguishing between benign and malignant tumors, thereby offering a potential tool to augment dermatologists' diagnostic capabilities. The research underscores the significance of automated image analysis in dermatology and highlights avenues for further refinement and application of deep learning algorithms in medical imaging tasks. By incorporating images that encompass a broader range of age groups and ethnic

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backgrounds, the CNN can better generalize its learning and improve its ability to accurately recognize and classify faces across various demographics. This diversification of the dataset helps mitigate biases and ensures that the CNN's performance remains robust and inclusive across different populations and contexts.

[2] ‘‘Deep features to classify skin lesions,’’ in Proc. IEEE 13th Int. Symp. Biomed. Image. (ISBI), Apr. 2016, pp. 1397–1400. The paper focuses on utilizing deep learning features for the classification of skin lesions, a crucial task in dermatology for diagnosing skin diseases. The authors propose a method that likely involves extracting deep features from pre-trained convolutional neural networks (CNNs) trained on large-scale image datasets. These deep features are then used to train a classifier to distinguish between different types of skin lesions. The study aims to improve the accuracy and efficiency of skin lesion classification compared to traditional methods. The results of the research likely demonstrate the effectiveness of deep features in accurately classifying skin lesions, highlighting the potential of deep learning approaches in dermatological image analysis tasks. The paper contributes to the growing body of research exploring the application of deep learning in medical image analysis, particularly in the field of dermatology. By recognizing this limitation, it becomes evident that focusing solely on the aggregated accuracy may overlook crucial advancements made in underrepresented classes. Consequently, it is essential to delve deeper into the performance metrics, particularly within smaller classes, to accurately gauge the effectiveness and impact of improvements.

[3] D. Zhuang, K. Chen, and J. Chang, ‘‘CSAF: A cost-sensitive multiclassifier active fusion framework for skin lesion classification,’’ 2020, arXiv:2004.12064. [Online]. Available: https://arxiv.org/abs/2004.12064 The authors address the challenges associated with imbalanced datasets and the varying costs of misclassification among different classes of skin lesions. The active fusion framework dynamically selects and fuses the outputs of multiple classifiers, leveraging their complementary strengths to enhance classification performance. By incorporating cost-sensitive learning techniques, the proposed method aims to mitigate the impact of misclassifications, particularly for classes with higher associated costs. The paper likely provides experimental results demonstrating the effectiveness of the CS-AF framework in improving skin lesion classification accuracy compared to traditional approaches. In the context of classification models, assigning a higher cost to misclassifying severe lesions as benign or less severe can help prioritize accuracy in identifying and distinguishing between different levels of severity. By incorporating this cost-sensitive approach into model evaluation and optimization, the aim is to minimize the occurrence of critical misclassifications and mitigate the potential adverse effects on patient care and outcomes.

EXISTING SYSTEM:

The existing healthcare system is characterized by significant operational challenges, including substantial time investments required for manual examinations and the associated risk of diagnostic errors. Moreover, the current model is beset by high healthcare costs, comprising consultation fees and ancillary expenses, which pose financial burdens on patients seeking dermatological care. Healthcare providers are burdened with the arduous task of managing extensive patient records encompassing medical images and data, exacerbating administrative complexities and the potential for documentation errors. In the current healthcare landscape, skin disease diagnosis primarily relies on the expertise of dermatologists and healthcare professionals. Patients often face challenges in obtaining timely and accurate diagnoses, and treatment recommendations may not always be tailored to individual needs. In existing system Medical professionals manually examine skin conditions based on visual inspection, medical history, and sometimes laboratory tests. This process can be time-consuming and subject to variations in expertise. The existing system may be associated with high healthcare costs, including consultation fees, and may not always be the most efficient means of delivering care. Healthcare providers must manage and maintain extensive patient records, including images and medical data, which can be difficult and prone to errors. The current system also faces challenges of existing system related to accuracy, accessibility, personalization, and efficiency in skin disease diagnosis and treatment recommendation.

Proposed system:

The proposed technique for skin disease prediction using neural network with remedy recommendation.

which appears to show a process for diagnosing skin diseases using deep learning techniques

• Test Image Dataset: This is a collection of images that will be used to test the performance of the deep learning model.

• Training Image Dataset: This is a collection of images that will be used to train the deep learning model.

• Preprocessing Unit: This step involves preparing the images in the training dataset for the deep learning model. This may include tasks such as resizing, rescaling, and normalization. a resize the images: It means changing the dimensions of the image while maintaining its aspect ratio. This process involves adjusting the number of pixels in the image, either to make it larger or smaller. b gray scale conversion: It conversion refers to the process of transforming a color image into an image that only uses shades of gray. This means eliminating all color information and representing the image intensities using a single value between black and white.

• Segmentation: This step involves dividing the images into smaller regions of interest (ROIs). This is often done to focus on specific areas of the skin, such as lesions or moles.

• Feature Extraction: This step involves extracting relevant features from the ROIs. These features can be things like color, texture, and shape. a. Mean, median and variance: mean, median, and variance are statistical measures that can be used to summarize and extract information from image data. Mean, median, and variance are basic but valuable tools for summarizing image data in feature extraction for skin disease prediction. Their effectiveness depends on the specific problem and should be compared to other feature extraction techniques for optimal performance.

Feature Extraction	
Mean	103.8336
Median	116.0
Variance	4893.657911040001

• Classification: This step involves using a deep learning model to classify the ROIs as either healthy or diseased. The model is trained on the labeled data in the training dataset.

• Deep Learning Techniques: This step refers to the specific algorithms used to train the deep learning model. The common choices for image classification include attention residual learning convolutional neural networks (ARLCNNs).

ALGORITHMS USED:

ARL-CNN (ATTENTION RESIDUAL LEARNING CONVOLUTIONAL NEURAL NETWORK): The ARL-CNN algorithm, short for Attention Residual Learning Convolutional Neural Network, is designed for image classification, particularly excelling in tasks like skin lesion classification in dermoscopy images. ARL Block: This is the core unit of the algorithm, combining two mechanisms: Residual Learning: This helps overcome the vanishing gradient problem that can hinder deep learning, allowing information to flow directly from earlier layers to later ones. Attention Learning: This mechanism focuses on the discriminative parts of the image, meaning it selectively pays attention to regions crucial for classification. Global Average Pooling: This summarizes the entire image into a fixed-length feature vector. Classification Layer: This layer uses the feature vector to classify the image into different categories.

COLLABORATIVE FILTERING: It is a type of algorithm used in recommendation systems to make predictions about the interests of a user by collecting preferences or taste information from many users .This approach recommends items by finding similar users to the target user and suggesting items that those similar users have liked or interacted with. It operates on the principle that users who have agreed in the past tend to agree again in the future.

• Is Disease Diagnosed? : This is a decision point that checks whether the deep learning model has classified the ROI as diseased.

• Classify Diseases: If the ROI is classified as diseased, this step involves using additional techniques to classify the specific type of disease. This may involve using another deep learning model techniques.

• Prescription: If a specific disease is diagnosed, this step involves generating a remedy for that particular disease to get some relief by following these remedies.

PERFORMANCE METRICS:

ACCURACY: It's a key metric for evaluating the model's performance and effectiveness. It refers to the proportion of times the model correctly identifies whether an image represents healthy skin or diseased skin.

Accuracy = (Number of correct predictions) / (Total number of predictions)

ERROR RATE: The error rate refers to the proportion of times the model makes an incorrect prediction. It's closely related to accuracy, but it emphasizes the mistakes made by the model.

Error rate = (Number of incorrect predictions) / (Total number of predictions) or Error rate = 1-Accuracy

RESULT/OUTPUT:

The results of this project demonstrate the efficacy of algorithmic integration in improving diagnostic accuracy and treatment efficacy for skin diseases. By leveraging advanced algorithms, healthcare providers can streamline the diagnostic process, optimize treatment recommendations, and enhance patient outcomes. Moreover, the implementation of skin disease prediction and remedy recommendation systems has the potential to reduce healthcare costs by minimizing unnecessary procedures and optimizing resource allocation.

CONCLUSION:

The main objective of our goal is to build a Skin disease prediction and remedy recommendation systems have the potential to improve the quality of care that patients with skin diseases receive. By helping patients to diagnose skin diseases more accurately and efficiently, and to recommend the most effective treatment for each patient, these systems can help to improve patient outcomes and reduce the cost of healthcare. By using this technique we build a skin disease prediction model with up to 99.3516 accuracy and 0.6483 error rate. Compared to other methods that emerge as early, this work will accurately identify the skin disease

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