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Nail Disease Detection System

Sagari J[1], Thanvi HV[2], Samrudhi[3], Mrs.Amrutha Bhat[4], Shwetha K R[5]

[1,2,3,4,5]Computer Science & Engineering Mangalore Institute of Technology & Engineering, Moodabidre, India

Abstract

Nail diseases are becoming an increasing health concern and can sometimes indicate underlying medical conditions. This paper presents a deep learning–based system developed to detect and classify nail diseases using digital images. The proposed approach uses the ResNet-18 Convolutional Neural Network (CNN) architecture to analyze nail images and identify disease patterns based on visual characteristics such as color, texture, and shape abnormalities. The residual learning capability of ResNet-18 helps the model extract important features efficiently while reducing training complexity, leading to improved accuracy and faster convergence. The system is implemented as a user-friendly web application using the Flask framework, where users can upload nail images and receive diagnostic results in real time. By providing an accessible and reliable tool, the system aims to assist both healthcare professionals and individuals in the early detection and monitoring of nail-related conditions, thereby supporting preventive healthcare and improving dermatological assessment.

Keywords: Deep Learning, Convolutional Neural Network (CNN), ResNet-18, Nail Disease Detection, Nail Image Classification, Healthcare AI.

INTRODUCTION

Nail diseases are common dermatological conditions and can sometimes indicate underlying health problems such as diabetes, anemia, or heart disease. However, early and accurate detection can be challenging because many nail diseases show similar visual symptoms. In most cases, diagnosis depends on manual examination by medical professionals, and sometimes additional laboratory tests are required. These traditional approaches can be time-consuming and largely depend on the experience and judgment of the doctor, which may occasionally result in delayed or inaccurate diagnosis.

The increasing number of nail disorders is also influenced by factors such as lifestyle changes, environmental pollution, and various health conditions. As the variety and complexity of nail diseases continue to grow, accurate diagnosis becomes more difficult due to overlapping symptoms and emerging variations. This problem is even more serious for individuals who do not have easy access to dermatologists, as they often rely only on visual self-inspection, which can be subjective and prone to human error. In addition, limited awareness about early symptoms and preventive care often delays medical attention, allowing minor nail problems to develop into more severe conditions. The shortage of dermatology specialists, particularly in rural and developing regions, further restricts access to proper diagnosis and treatment. Although artificial intelligence and computer vision technologies have made significant progress, accessible and reliable digital tools for automated nail disease detection are still limited in real-world healthcare settings. As a result, many patients may continue to face delays in diagnosis and treatment, which can negatively affect their overall health and quality of life.

RELATED WORKS

Research on nail disease detection has progressed significantly with the development of artificial intelligence, machine learning, and deep learning techniques in medical image analysis. Earlier approaches mainly relied on traditional image processing and machine learning algorithms such as Support Vector Machines (SVM) and Random Forest to classify nail diseases. Although these methods provided basic classification capabilities, they required manual feature extraction and often struggled to capture complex visual patterns in nail images, which limited their accuracy and practical applicability.

Recent studies highlight the effectiveness of deep learning models, particularly Convolutional Neural Networks (CNNs), in improving disease detection performance. Shandilya et al. [1] proposed an automated nail disease detection system using a Hybrid Capsule CNN model capable of classifying six categories of nail conditions, including clubbing, melanoma, onychogryphosis, pitting, blue finger, and healthy nails. Their model combined CNN-based feature extraction with Capsule Networks to preserve spatial relationships in nail images, achieving an accuracy of 99.25% on a dataset of 3,835 images. However, the approach required significant computational resources and lacked validation in real-world clinical environments.

Similarly, Ardianto et al. [2] developed a deep learning model that integrates medical imaging data with bioinformatics information to diagnose multiple nail diseases. Their system applied preprocessing techniques such as normalization, resizing, and contrast enhancement to improve image quality before classification. The CNN-based approach achieved an overall accuracy of 83% across 17 nail disease categories. Despite promising results, the study reported challenges related to limited and imbalanced datasets, which affected the detection performance for rare conditions.

Nijhawan et al. [3] proposed an integrated deep learning framework combining multiple CNN architectures to classify 11 nail disease classes. The model was trained on 4,190 nail images and achieved an accuracy of 84.58%, outperforming traditional machine learning methods such as SVM, K-Nearest Neighbors, and Random Forest. Although the framework improved classification performance, it required substantial computational resources and faced limitations due to dataset diversity.

Despite these advancements, most existing studies focus primarily on improving model accuracy under controlled research conditions. Few systems provide real-time, accessible platforms for practical use by healthcare professionals or individuals. Additionally, challenges such as limited datasets, variations in image quality, and lack of clinical validation continue to restrict the deployment of AI-based nail disease detection systems in real-world healthcare settings. The proposed work aims to address these limitations by developing a deep learning–based nail disease detection system integrated into a web-based application for accessible and efficient diagnosis.

IMPLEMENTATION

A. System Design and Workflow

The Nail Disease Detection System is developed using a combination of modern technologies to ensure accurate disease detection, efficient system performance, and an accessible user interface. These tools help integrate the deep learning model, backend services, and the web-based user interface.

Python is used as the primary programming language for backend development and for implementing the deep learning model. It is widely used in artificial intelligence and machine learning applications due to its simplicity and extensive ecosystem of libraries.

PyTorch and Torchvision are used to build and fine-tune the ResNet-18 Convolutional Neural Network

(CNN) model. These frameworks provide powerful tools for training deep learning models and enable efficient feature extraction from nail images for disease classification.

Flask is used as the backend web framework to manage the interaction between the user interface and the deep learning model. It handles tasks such as receiving uploaded images, processing requests, performing model inference, and returning prediction results to the user.

MongoDB / MySQL is used as the database system to store user information, prediction records, and historical detection results. This enables the system to maintain organized data storage and allows users to access previous diagnostic reports.

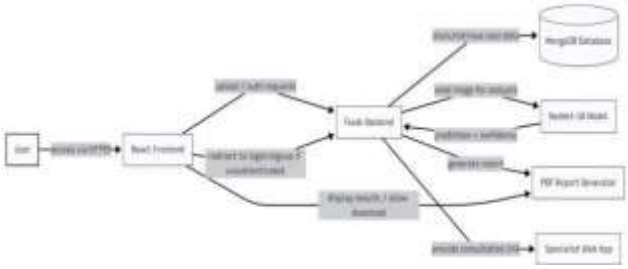

Fig. 1. Architecture of the proposed Nail Disease Detection System

B. Hardware and Software Requirements

The Nail Disease Detection System requires moderate hardware and software resources for efficient operation. A system with at least an Intel Core i5 or AMD Ryzen 5 processor, 8 GB RAM, and 256 GB SSD is recommended for smooth performance. For faster model training and prediction, a GPU such as NVIDIA GTX 1650 can be used. The system is developed using Python and supports operating systems such as Windows, Linux, and macOS. The deep learning model is implemented using PyTorch and Torchvision, while Flask is used for backend services. The frontend interface is created using HTML, CSS, and JavaScript to provide a responsive web-based platform

C. Application Workflow

The system follows a simple workflow to provide real-time nail disease detection. Users upload a nail image through the web interface, which is then sent to the server for processing. The trained ResNet-18 deep learning model analyzes the image and identifies the possible nail disease based on visual features. The system then displays the predicted disease along with a confidence score and basic recommendations. This workflow allows users to quickly obtain results and better understand their nail health condition.

D. Deep Learning Model (ResNet-18)

The core component of the system is the ResNet-18 Convolutional Neural Network (CNN) model, which is used for nail disease classification. The model is fine-tuned using a dataset of nail images that include both healthy and diseased conditions. During training, the model learns to recognize important visual patterns present in nail images.

By analyzing these patterns, the model identifies key features such as color changes, texture variations, and abnormalities in nail shape. Based on these learned features, the system can accurately classify different nail diseases, including Onychomycosis, Melanonychia, Pitting, Clubbing, and Beau's Lines. This enables the system to provide reliable predictions for early disease detection..

E. Frontend and Backend Integration

The system follows a client–server architecture in which the frontend and backend components work

together to ensure smooth and efficient operation. The backend is developed using Python and Flask, which handles tasks such as receiving uploaded nail images, processing the data, and performing predictions using the trained deep learning model.

The frontend is developed using HTML, CSS, and JavaScript, providing a simple and user-friendly interface for users. Through this interface, users can easily upload nail images and view the prediction results. This design helps create an interactive and accessible web application for nail disease detection.

F. Performance Optimization and Deployment

The system is designed to deliver efficient performance while requiring minimal computational resources. The lightweight ResNet-18 model enables the application to run smoothly on standard computers without the need for high-end hardware or specialized equipment.

Additionally, the system can be deployed on local servers or cloud platforms, making it flexible and easily accessible. This deployment approach supports scalability, allowing multiple users to access the application and benefit from nail disease detection services.

RESULTS AND DISCUSSION

The Nail Disease Detection System was successfully designed, developed, and tested as a functional web-based application. The system uses deep learning techniques to automatically detect and classify nail diseases from uploaded images. This section demonstrates how the developed system works in practice and evaluates its effectiveness in identifying different nail conditions.

The system was tested using multiple nail images representing different disease categories. Experimental results show that the trained ResNet-18 Convolutional Neural Network (CNN) model is capable of accurately recognizing visual patterns in nail images and providing reliable predictions. The integration of the web interface with the deep learning model allows users to upload images and receive results in real time, making the system accessible and easy to use.

A. System Design and Workflow

The system follows a structured workflow that enables users to detect nail diseases through a web application. The process begins when a user uploads a nail image via the web interface, after which the image is sent to the backend server for processing. The system prepares the image and forwards it to the trained ResNet-18 Convolutional Neural Network (CNN) model for analysis. The model examines the visual patterns in the image to identify possible nail diseases. Finally, the system displays the predicted disease along with its confidence level, helping users understand the potential condition of the nail.

B. Disease Classification Using ResNet-18

The core component of the system is the ResNet-18 Convolutional Neural Network model, which is used to classify nail diseases. The model is trained using a dataset of nail images representing different disease conditions. During training, the model learns important visual features that help distinguish between healthy and diseased nails.

By analyzing characteristics such as color variations, texture patterns, and abnormalities in nail shape, the model can identify several nail diseases. These include Onychomycosis, Melanonychia, Pitting, Clubbing, and Beau's Lines, enabling the system to provide accurate predictions and assist in early detection.

C. Web Application Integration

The system is implemented as a web-based application to make it accessible and easy to use. The backend is developed using Python and Flask, which handles image uploads, processes user requests, and

performs disease prediction using the trained deep learning model.

The frontend is built using HTML, CSS, and JavaScript, providing a simple and interactive interface. Users can upload nail images and quickly view the prediction results, making the system convenient for both healthcare professionals and general users.

D. System Performance

The system is designed to deliver efficient performance with minimal computational requirements. The lightweight ResNet-18 model enables the application to run smoothly on standard computers without requiring high-end hardware.

In addition, the system can be deployed on local servers or cloud platforms, allowing multiple users to access the application simultaneously. This makes the solution scalable and suitable for real-world healthcare applications.

CONCLUSION

The Nail Disease Detection System was developed to provide an intelligent and accessible solution for identifying common nail disorders using deep learning techniques. The system utilizes the ResNet-18 Convolutional Neural Network (CNN) model to analyze nail images and detect visual features such as color changes, texture variations, and abnormalities in nail shape. Through the integration of a web-based interface, users can easily upload nail images and receive quick diagnostic results. This approach helps overcome the limitations of traditional manual diagnosis, which often relies on visual inspection and expert judgment.

Experimental evaluation indicates that the system can effectively identify different nail diseases, including Onychomycosis, Melanonychia, Pitting, Clubbing, and Beau's Lines. By combining artificial intelligence with a simple web application, the system enables faster and more reliable disease detection, supporting early diagnosis and preventive healthcare. In the future, the system can be enhanced by expanding the dataset, improving model accuracy, and developing mobile-based or cloud-based versions to increase accessibility and practical use in healthcare environments.

In conclusion, the proposed Nail Disease Detection System demonstrates how deep learning and web technologies can be effectively used to provide fast, reliable, and accessible identification of common nail disorders, supporting early diagnosis and improved healthcare monitoring.

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