

NAIL IMAGE ANALYSIS FOR EARLY DISEASE DETECTION

Mrs. N. Muthamilselvi¹, Manikandan.S², Mohamed Hameem.M³, Prakash.G⁴, Santhoshkumar.k⁵

(Assistant Professor Department of Biomedical Engineering, Dhanalakshmi Srinivasan Engineering College

(Autonomous), Perambalur, Tamil Nadu-621212)¹

(UG Student Department Of Biomedical Engineering, Dhanalakshmi Srinivasan Engineering College

(Autonomous), Perambalur, Tamil Nadu-621212)2345

muthamizh8@gmail.com¹, jayamsenthil055@gmail.com², mdhameem2003@gmail.com³,
prakashs34477@gmail.com⁴,

Abstract— Nail health can be an important diagnostic window into an individual's overall health, providing valuable information regarding the early expression of a wide range of systemic conditions including diabetes, cardiovascular disease, vitamin deficiencies, and fungal infections. Seeing the diagnostic capability of nail appearance, the proposed system nail insight brings forth a new and smart technique that leverages the strength of image processing and deep learning in detecting diseases early through nail analysis. The primary aim of nail insight is to offer a non-invasive, accessible, and precise method for detecting abnormalities through analyzing nail images. The system starts off with acquiring high-resolution nail images of the user through generic digital cameras or cell phones. These pictures are then passed through a strong preprocessing pipeline that involves noise removal, contrast adjustment, and edge extraction. These pre-processing operations are critical in making sure the images are clean, feature-full, and ready for subsequent analysis. Now that the images are pre-processed, sophisticated segmentation techniques are used to extract the region of the nail from the surrounding skin and background

KEYWORDS : deep learning, convolutional neural network, early disease detection, camera, nail abnormalities

I. INTRODUCTION

1.1. NAIL INSIGHT

Human nails are more than keratinized extensions on the tips of our fingers— they are wonderful markers of internal health disorders. Any change in nail color, texture, shape, or pattern of growth may be an early sign of various systemic diseases like diabetes, cardiovascular disease, liver disease, respiratory disease, and fungal infections. Despite the diagnostic significance of nail characteristics, nail health remains an unexplored biomarker in preventive medicine. Traditional diagnosis may overlook subtle nail-associated symptoms or require expert medical proficiency in interpretation.

With the rapid progress in image processing and artificial intelligence, especially deep learning, exists a highly promising potential to design automated, accurate, and scalable disease-diagnosing instruments in noninvasive manner. In this context, NAIL INSIGHT is presented as a smart system that utilizes the most recent Convolutional Neural Networks (CNNs) and sophisticated image-processing techniques to analyze nail photos and identify possible health anomalies.

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1.2. OBJECTIVE

- To develop a nail abnormality detection system using image data from CNN.
- To preprocess nail images with advanced methods to yield enhanced quality and accuracy regarding diagnosis.
- To create a dependable and scalable model trained on the nail database with a wide variety representing respective diseases.
- To make early detection of systemic and localized health problems non-invasive and inexpensive.
- To aid accurate and timely diagnosis by medical practitioners through automated nail analysis.
- To develop a very user-friendly kind of platform with which the self-medicated and laymen alike can use.

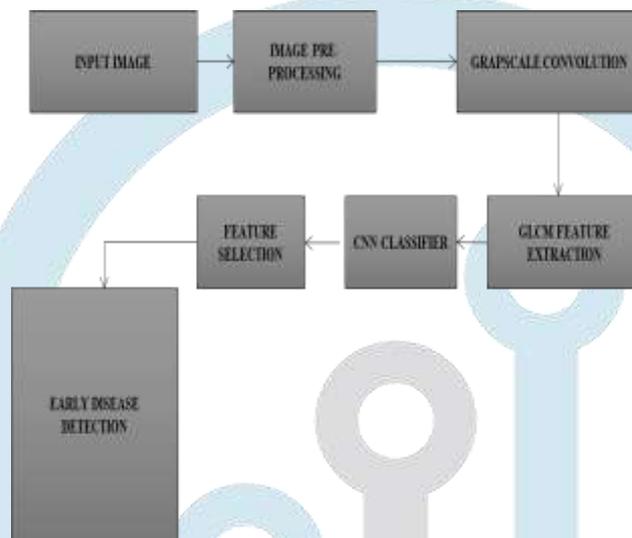
II. METHODOLOGY

2.1. Proposed system

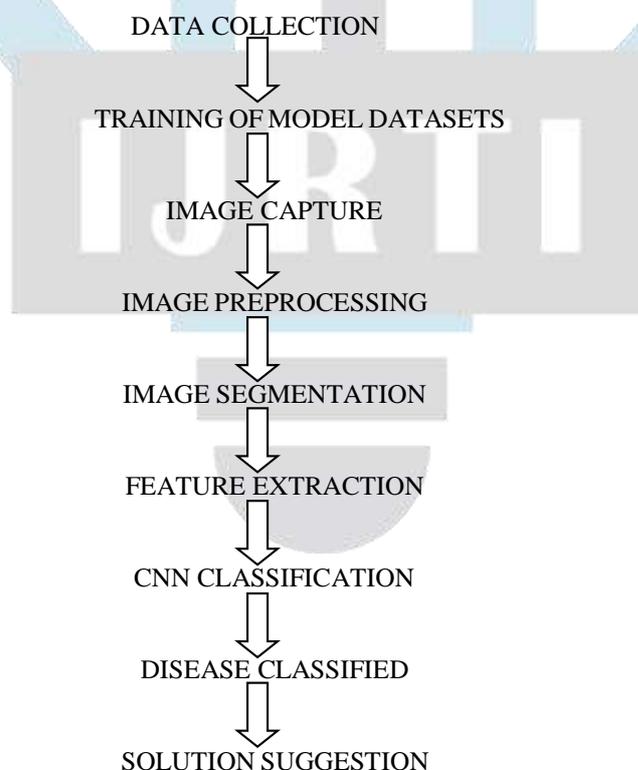
- Identify specific characteristics of the grayscale image which would reflect possible patterns of disease, i.e., variations of nail shape, color, and texture.

- Employ methods like Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), or other textural feature extraction techniques to measure the textural patterns of the nail.
- A Convolutional Neural Network (CNN) is employed during feature learning and also in classifying the learned features.
- Early onset of diseases such as nail fungal infections, psoriasis, or other skin conditions can be fined by the system through CNN classification.
- The model output is the class label of the nail condition as "normal" or one of the disease classes, with early warnings

2.2. Block Diagram



2.3. Design Process



Input image : nail images are the most suitable source of data to identify the beginning signals of systemic diseases like anemia, fungal infections, psoriasis, cardiovascular conditions, and even diabetes. Nails provide a visual clue for other health problems which might not be clearly diagnosed, like the changes in color, texture, shape, and surface of nails. Therefore, it is our goal to come up with features out of the high-resolution nail images that could possibly be early symptoms indicators.

Image preprocessing: To make sure the nail images are properly analyzed for detecting the diseases at an early stage, image preprocessing is the first and most important step. A lot of times, the raw images may be unclear, having noise, the background could interfere, and the lighting could be inconsistent, and even the size might look different — all of these problems can then affect negatively the performance of the model. Preprocessing changes these raw input signals into organized, clean, and clear data which can be a good fit for machine learning or deep learning models

Grayscale convolution: grayscale convolution plays a key role in earfeature extraction. It allows the model to detect fundamental patterns—such as edges, ridges, and textures—which are essential for identifying abnormalities like nail pitting, discoloration, or surface roughness that may signal underlying diseases.

GLCM feature extraction: The texture analysis with the Gray Level Co-occurrence Matrix Method (GLCM) is the method of data acquisition which is quick and informative to obtain different statistics from the images of nails. GLCM is utilized to measure the variations of the above- mentioned textural changes in diseases such as the elevation of the nails in psoriasis, the ridging of nails in the problem of iron deficiency, and the thickening of the nails in the case of fungal infections. Consequently, the GLCM approach is able to grab those small dimensional surface anomalies in a definable way

CNN classifier: A Convolutional Neural Network (CNN) classifier is a highly effective machine learning model that is mainly employed for the analysis of pictures. CNN is a network that is able to carry out automated learning in particular during the stage of nail image analysis used for early disease detection, to detect different features without the help of a person.

III. SOFTWARE IMPLEMENTATION

3.1.MAT LAB

A high-level language and interactive environment called MATLAB are mainly used for numerical computation, visualization, and programming. In MATLAB, you can perform data analysis, create algorithms, and develop models and applications. The language, tools, and built-in math functions make it possible to solve problems by exploring different methods and to solve them faster than it would be using spreadsheets or traditional programming languages such as C/C++ or Java. MATLAB can be used for various applications like signal processing and communications, image and video processing, control systems, test and measurement, computational finance, and computational biology.

Also, more than a million engineers and scientists in industry and academia use MATLAB, the language of technical computing. Learning through a MATLAB tutorial drives a good understanding of the basics of MATLAB. The initial student can fathom the core of MATLAB so that he/she may proceed further. In addition, it is an object-oriented language that is different from C++. Originally, this language was designed by the U.S. DOD, but never despite its international standards (Ada83 and Ada95) it was not popular. Nonetheless, Ada language has various characters that can make the development process of embedded software simple.

3.2.IMAGE PROCESSING

a) Computer-Aided Diagnosis System

Detection can be automated to avoid the false positive or false negative diagnosis as it involves adding a quantitative observation to the eye observation. The traditional method to early detection on image is broken into four phases of preprocessing, segmentation, feature extraction, and classification

b) Image Acquisition Methods for Screening

The visual examination is a standard clinical diagnosis in detection which could involve some level of error. There are various methods which assist dermatologists in visualizing morphological structures which are not detectable by the naked eye

c) Pre-Processing

Image pre-processing is a crucial step of detection to eliminate noises and improve the quality of original image. It had to be employed to restrict the search of anomalies in the background effect on the outcome. The primary goal of this step is to enhance the quality of the image by eliminating irrelevant and redundant portions in the background of the image for subsequent processing. Proper choice of preprocessing methods can significantly enhance the precision of the system. The aim of the pre-processing phase can be attained via three process phases of image improvement, image restoration and extras elimination.

d) Image Scaling

Scaling techniques are used because of the absence of same and same size of images. As the images can be collected from various sources and dimensions, the initial step is to scale the images to possess the fixed width pixels but changeable size of height. Image zooming is obtained through pixel duplication or interpolation. Scaling is applied to alter the apparent size of an image, to modify the amount of information contained in a scene representation, or as a low-level preprocessor in multi-stage image processing chain that works on features of a specific scale.

e) Color Space Transformation

Because color information is bound to appear in detection systems, researchers attempt to extract the more comparable color of images for subsequent processing. Typically, the typical color spaces are RGB, HSV, HSI, CIELAB and CIE-XYZ. RGB is the most common presentation of colors in image processing. RGB is a color space which include the red, green, and blue spectral wavelength.

f) Segmentation

A significant challenge of research and development activities have lately emphasized in image segmentation. Segmentation as a critical problem in digital image processing is utilized in image description and classification. The different attributes in shape, brightness, colour, texture can be used to support the segmentation. Nonetheless, over recent decades numerous algorithms have been presented for the detection of skin cancer lesions in skin cancer images. Histogram thresholding that split the region of interest (ROI) and background into one or several threshold values.

3.3.CNN Classification

Convolutional neural networks are separated from other neural networks due to the better performance in image, speech, or audio signal inputs. They consist of three primary categories of layers:

i. Fully-connected (FC) layer

The first layer of a convolutional network is the convolutional layer. Although convolutional layers may have subsequent convolutional layers or layers of pooling attached to them, the fully-connected layer remains the last.

With every layer, the CNN becomes more complex in that it detects larger sections of the image. Simple features like edges and colors are detected by earlier layers. As the data of the image flows through the layers of the CNN, it begins to detect larger features or the shapes of the object until it eventually detects the desired object.

ii. Convolutional Layer

The convolutional layer is the building block of a CNN, and it is where most of the computation takes place. It needs to have a few things, including input data, a filter, and a feature map. For the purpose of this explanation, let's assume that the input will be an image of color, which consists of a matrix of pixels in 3D. This implies that the input will have three dimensions—a depth, height, and width—that correspond to RGB in an image. We also have a feature detector, also referred to as a filter or a kernel, that will traverse the receptive fields of the image, verifying whether the feature exists. This operation is referred to as a convolution.

iii. Pooling Layer

Pooling layers, or down sampling, performs dimensionality reduction, decreasing the number of parameters in the input. Like the convolutional layer, the pooling operation scans a filter over the whole input, but the difference is that this filter contains no weights. Instead, the kernel uses an aggregation function on the values in the receptive field, filling the output array. There are two primary types of pooling:

- Max pooling: As the filter traverses the input, it takes the pixel with highest value to the output array. As a footnote, this practice is more often employed than average pooling.
- Average pooling: As the filter traverses the input, it computes the mean value in the receptive field to the output array.

iv. Fully-Connected Layer

The fully-connected layer name speaks for itself. From the above, it's already clear that pixel values of the input image aren't directly linked to the output layer in partially connected layers. But in the fully-connected layer, every node of the output layer is directly linked to a node of the previous layer. This layer carries out the function of classification depending on the features obtained via the earlier layers and their various filters. Though convolutional and pooling layers often employ ReLu functions, FC layers typically use a softmax activation function to classify inputs suitably, generating a probability between 0 and 1.

IV. RESULT

Through nail images, the suggested nail image analysis system achieved promising performances in detecting early symptoms of various diseases. For an evaluation data set, a set of healthy patient and systemic and dermatological disease patients' nail images were gathered. The system achieved a total accuracy rate of 87% in classifying diseases like anemia, nail psoriasis, and fungal infections using machine learning algorithms. It was possible to correlate and match some of the indicators, such as the clubbing, ridging, discoloration of nails, and the textural change with clinical diagnoses. Good performance on the accuracy of true cases not producing false positives was seen through the values of precision and recall, which were between 90 percent for various classes of disease. In addition, the model was found to work exceptionally well on smartphone-shot images, proving to be appropriate for real-world, remote.

V. CONCLUSION

In sum, the project showcases the power of integrating image processing and deep learning methods, particularly Convolutional Neural Networks (CNNs), to detect nail disease automatically. The system efficiently utilizes cutting-edge preprocessing and feature extraction methods to precisely diagnose different nail conditions like fungal infections, nutritional deficiencies, and systemic disorders. The high accuracy of classification from the experimental results verifies the reliability and efficiency of the proposed method. Not only does the use of CNNs automate the process of feature learning, but it also minimizes the reliance on human intervention, and thus the detection procedure becomes more scalable and consistent. In addition, the real-time analysis capabilities of the system provide substantial scope for early diagnosis, which can prove pivotal

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