Nails Deformation Sensing For Disease Detection Using Fusion Method For Texture Analysis

Vinaya Dehankar
Department of Electronics Engineering, Shri Ramdeobaba College Of Engineering And Management, Nagpur, India, dehankarvu@rknec.edu

Dr Shilpa Deoke
Department of Medicine, NKP Salve Institute of Medical Science & Lata Mangeshkar Hospital , Nagpur

Sujesh Gathe
Department of Electronics Design Technology., Shri Ramdeobaba College Of Engineering And Management, Nagpur, India, gathesr@rknec.edu

Dr Richa Khandelwal
Department of Electronics Engineering, Shri Ramdeobaba College Of Engineering And Management, Nagpur, India, khandelwalrr@rknec.edu

Abstract

Medical image processing is essential for identifying conditions like skin cancer, brain tumors, breast cancer, and illnesses of the heart and lungs. To detect disorders, the human nail serves as a window into the body. Various methods are available in the healthcare industry for early disease diagnosis. One method for diagnosing diseases in their early stages is nail image analysis. It is possible to forecast some general and dermatological disorders using human nails. The naked human eye cannot detect numerous variations in nail color or texture. In this research, models for illness prediction using nail pictures are constructed. In this work, the fusion of statistical and structural texture features is employed to forecast diseases. Merging structural and statistical features allows for the analysis of the correctness of many models and the selection of the most relevant one. Numerous methods, particularly GLCM, LBP, and Gabor filter, were used to combine statistical and structural features.

Keywords: nail images, fusion, structural, statistical, GLCM, LBP, Gabor

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I. Introduction

Numerous techniques have been created to diagnose diseases in the human body as a result of the rapid advancements in medical science. Nail colour and texture identification is one of these methods, along with pathological diagnostics. Even if the aforementioned processes yield precise results, carrying them out is very costly and time-consuming. As an illustration, taking a blood sample for a forensic test is rather unpleasant. The colour and texture of human nails can be used to indicate numerous disorders in the healthcare field.[1-3]. The inner layer of nail is where the alterations are most frequently found, making it a crucial component of the disease's diagnosis. The selection of elements for the nails that can be employed for diagnostics relies on your requirements. Many illnesses can change the texture of the nails. Normal healthy nails have a soft, shiny, and smooth appearance; however, diseases and illnesses can leave the nail surface with brittle, rough, pitted, vertical lines, etc. [2] Because minor changes in the texture of a few pixels of the nail are not noticed by the human eye, they can lead to incorrect results. In the past, using the colour characteristic had been a more widely used method for illness detection through images of nails. For example, a change in a person's nail colour can be used to detect certain diseases. A system was presented that would extract the colour characteristics of the human nail, determine the average RGB value of the nail colour, and then categorize the average RGB values to determine the condition [4].

The proposed system or model is being developed to detect the disease based on nail texture. The type of disease can be identified by a change in texture or deformity; for instance, clubbing in the nails is an indication of AIDS in its early stages. An indication of anemia may be spooning or koilonychia.[5] For the proposed model, a dataset with four classes—rough nails, brittle nails, pitted nails, and vertical lines on nails—was used to build the model. The algorithm of the suggested system is built to capture an image of the nail, perform image processing to isolate the precise nail region from the surrounding image, then apply a texture detection approach to the segmented nail part to determine whether the nail is healthy or not.[3] This algorithm is being developed so that it will automatically diagnose the disease after taking the input image, in contrast to the pathological tests, which require a lot of patience because they can take up to 24 hours, are painful, and require the patient to be present, while the proposed system only requires the image of a fingernail and could be sent over the internet. Since all that is needed to operate our system is an image of a nail, even laymen can use it. The goal of this research is to create a tool that can detect disease in people before it becomes critical, making it easier and affordable to treat.

Making a model for each type of texture discovered in the data set is the objective of the first stage, the feature extraction phase. The texture of the prototype image is first examined using the same method as in the subsequent operation. When the testing picture is verified to the train image, its classification is determined. The second step is the ranking process. [6]

Related Work:

Statistical textural feature analysis:

A. Pixel value spot localization is a procedure employed in certain machine vision algorithms that incorporate statistical texture processing. These techniques are used to evaluate the texture and execute a few statistical tests on the pixel-level brightness distribution functions. These tactics encompass first-, second-, and higher-level statistical features. The top-level single pixel specification differs from the other two in that it is determined without taking into account the interaction of the image pixels. [7]

Histogram Features and specifications: First-order statistical indicators are derived from the calculation of the statistical moments of the histogram of the image, and they are usually determined directly from the grey level of the pixels in the original image. The chart is just a graphical representation. It indicates the optical content of the image, or how much light and shadow there is in the image.

Co-occurrence Matrix: The grayscale co-occurrence matrix has been discussed by many researchers to derive features for texture classification [6]. To better maximize the detail provided in the co-occurrence matrix calculated for different distance parameters.[7] A well-known method for using statistical distributions to extract quadratic statistical texture features is GLCM. The five GLCM texture characteristics we use here: Contrast, Correlation, Difference, Energy and Homogeneity.[8]

Local Binary patterns: Local binary patterns (LBP) are a class of visual descriptors used in computer vision for categorization. The Texture Spectrum concept, first presented in 1990, has a specific use in LBP. Since then, it has been discovered to be a potent feature for texture classification, and it has also been discovered that the combination of LBP with the Histogram of Oriented Gradients (HOG) descriptor significantly enhances detection performance on specific datasets. [9-10]

Local Gabor Patterns: To use the Gabor-based procedure, the images are usually convolved with a set of 40 filters before being worked with directly on their absolute values. The Gabor transform is comparable to the wavelet transform in these Gaussian-based functions; therefore, this transformation is ideal in frequency domain configurations. [11] The Gabor wavelet is the best transform for reducing the two-dimensional uncertainty connected to the frequency and position domains. A mixed sinusoidal function and a Gaussian modulus function combine up a two-dimensional Gabor. Gabor filters have been extensively used in a variety of computer vision applications, including edge recognition and texture analysis. Below is a table representing a linear and local filter, the Gabor filter.[12]

Individual method	Combination of different methods
Local Binary Pattern GLCM Gabor filter Wavelet Transform	Binary Gabor pattern. Gabor and LBP. Wavelet transform and GLCM.

Structural textural feature analysis:

Edge feature: In a particular area of the image, it is the limit of two grey levels or the brightness value of two neighboring pixels that is the highlight. To locate the areas of an image where the intensity of the light abruptly fluctuates, edge detection is used.[13]

SIFT: In 1999, David Loo introduced this concept. It is distinguishable and has good occlusal accuracy. The first task is to select the image areas of focus. The areas of the image where the Difference of Gaussian (DoG) is maximal or minimum are the vital areas.

Categorization of texture using structural methods:

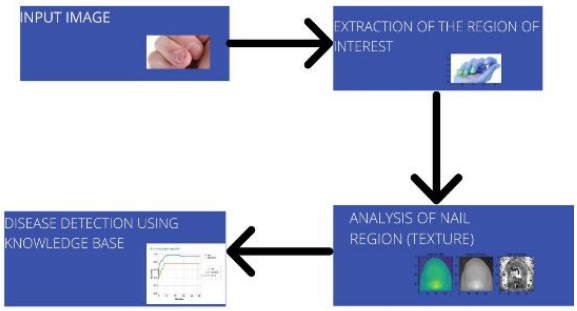
Individual Method	Combination of different methods
HOG Morphological Filter SIFT	Edge-based texture granularity detection

Fusion of Statistical and Structural Feature

Feature merge helps to fully understand the features of the images to describe their rich internal information, and after reducing the size we can get a compact presentation of the features. embedded, thus reducing computational complexity and better performance with unrestricted environments. Three merged features - GLCM and SIFT, LBP and SIFT, Gabor and SIFT - were used in our experiments. GLCM and SIFT provide the highest accuracy out of all of these.[14]

When applying different image alterations using feature descriptors, the main objective of image matching is to determine the precise matches between two photographs of defined IP addresses (such as lighting, fine-tuning and compression). Several methods have been used to extract IP addresses from photographs, including The SIFT descriptor yields the best detection results, according to the authors of [8]. It is comparatively stable and slightly light- and image-modification-invariant, including translation, scaling, and rotation. Many suggestions for SIFT method enhancements have been made, including PCA-SIFT.

II. METHODOLOGY:



A. Dataset*Figure1: Flow chart*

In diseases, illness is detected by the nail's appearance. Thus, we have divided the data set into 4 categories of patterns detected as an ill nail as done in [14]. four different classes of Nail images are used for this experiment total of 30 samples are collected for each category.

In order to further investigate, enhance, and boost the accuracy of our model, we acquired a real-time dataset for our study. We gave a visit to Nagpur and went to the NKP Salve Institute of Medical Science and Lata Mangeshkar Hospital, where we took images of the fingernails of 28 patients receiving care in the wards. This met our aim of applying our approach in real-time. A total of 180 images were collected. Images obtained and discovered online made up the other dataset that was utilized. Because the light condition is the most important aspect in image processing, we must keep the light condition consistent for each image we extract in order to achieve accurate results in detecting and determining the Region of interest [6]. So, to keep light conditions similar we have designed a small box with a light inside so that we get the same intensity of light for every image. The setup is shown in the following figure.

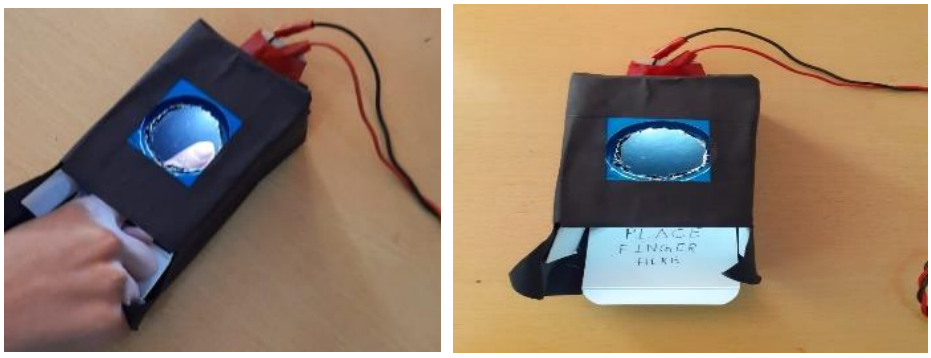
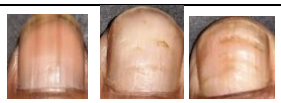
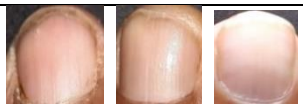


Fig 2-Setup

Table 3: Heterogenous dataset

Class	Virtual Dataset	Real time dataset
Brittle Nails		
Rough Nails		
Pitted Nails		
Vertical lines on Nails		

A. Extraction of Region of interest (ROI)

This research will classify between the nail portion and the non-nail portion. The resolution of the image shown is 500x800 pixels,we are using open-cv and TensorFlow to detect the region of interest in the given picture[5].

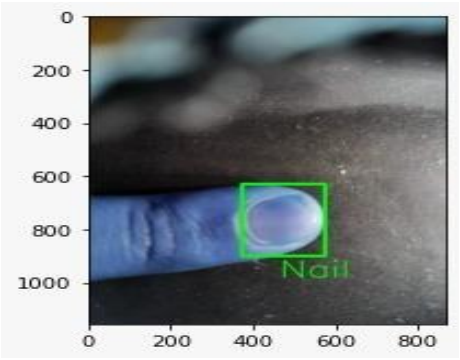


Fig 3- Nail detection using image processing

B. Analysis of nail region (Texture analysis)

To test the estimated classes against the original classes, the estimated classes are modified, and the recognition rate is computed to assess how well the approach was implemented. The effectiveness of each algorithm is then evaluated in respect to other accessible techniques using the recognition rate of each algorithm.

$$\text{Classification accuracy} = \frac{number\ of\ correct\ matches}{total\ number\ of\ test\ images} x100$$

a. Statistical textural feature analysis:

i.Co-occurrence matrix:

Given an image, I, of size N x N, the co-occurrence, matrix P can be defined as

P (i, j)
=
$$\sum_{x=1}^{N}\sum_{y=1}^{N}\begin{cases}1, & if\ I(x,y)=i\ and\ I(x+\Delta x, y+\Delta y)=j\\ 0, & otherwise\end{cases}$$

$(\Delta x, \Delta y)\ is\ specifically\ the\ distance\ between\ the\ pixel-of-intrest\ and\ its\ neighbour$

The offset $(\Delta x, \Delta y)$ parameterization makes the co-occurrence matrix sensitive to rotation [6].

To obtain some translational regularization, we employ the displacement sweeping across 180 degrees at the same distance parameter (i.e., [0,] for 0 degrees: P horizontal for 45 degrees of [-] P right diagonal for a 90-degree angle: and [- for 135 degrees with P parallel.: left diagonal[15]

Contrast

It measures the conflict between a pixel and its neighbor in the sense of intensity in the entire image [10].

$$\text{Contrast} = \sum_{i,j=0}^{N-1} P_{ij}(i-j)^2$$

Correlation

It measures linear relationships in a grayscale in an image.

$$\text{Correlation} = \sum_{i,j=0}^{N-1} P_{ij}\frac{(i-\mu)(j-\mu)}{\sigma^2}$$

Energy

Energy defines the uniformity in the image. It gives the sum of square elements in the GLCM matrix.

$$\text{Energy} = \sum_{i,j=0}^{N-1}(Pij)^2$$

Homogeneity

It talks about how identical pixels are. pictures in a homogenous GLCM grid given its values as 1.

$$\text{Homogeneity} = \sum_{i,j=0}^{N-1}\frac{Pij}{1+(i-j)^2}$$

ii.Local binary pattern

The Clustering algorithm was first intended to describe textures. By thresholding the 3x3-neighborhood of each component with its core pixel value and using the outcome as a binary integer, the operator provides a label to each pixel of an image (gives 0 if each pixel is smaller than the center, otherwise 1). The label histogram could then be employed as a decision surface.[16]

iii.Local Gabor pattern

A complicated exponential and Gaussian function, Gabor filters, by utilizing the Gabor filter, BGP, also known as the binary Gabor Pattern [17], was able to enhance LBP. It functions by initially employing the same eight Gabor filters. Only the direction of these filters differs. Following the application of these filters, an eight-dimensional image fragment is generated. Even though these values are binary, the algorithm's next step resembles a spatially insensitive local binary pattern.

b. Structural textural feature analysis

Histogram Features and specifications:

Given a total of 500×500=250.000 pixels. Multiplied by 3 (for each colour), this gives a total of 750.000 different values to code this image. This number is way too big to be used the same way we used the different AIS features, we need a method to extract bigger information from the picture, and have less attributes to perform a machine learning experiment. The method we use to get the HOG descriptors for an images takes several parameters which we can change, including the number of different directions the lines should take and the size of the blocks. [16] as follows:

$$\mu n(x) = \sum_{i=0}^{L-1}(xi-m)^n p(xi)$$

Scale Invariant feature transform (SIFT):

A SIFT *key point* is a circular image region with an orientation. It is described by a geometric *frame* of four parameters: the key point centre coordinates *x* and *y.* SIFT detector uses as key points image structures which resemble "blobs". By searching for blobs at multiple scales and positions, the SIFT detector is invariant (or, more accurately, covariant) to translation, rotations, and re-scaling of the image, as a conclusion, the scale space is known as.[18]

- Key point localization
- Key point descriptor

c. Fusion of structural and statistical feature

RANSAC or Random Sample Consensus [13] is used to remove outliers in each cluster to compute accurate homographic matrices for matched points. In this technique, a random set of points (3 points for the proposed method) are taken to compute homographic*.*
In this step, we applied the matching between the Ips descriptor with the nearest neighbour method using the Euclidean distance.

GLCM and SIFT:

To eliminate false matching, a novel SIFT-based technique is used in this research that uses a grey-level co-occurrence matrix to refine the observed matches. The grey-level co-occurrence matrix found for the SIFT major point cluster is applied to generate the contrast level between the genuine and fabricated regions, whose difference is used as a similarity index. The suggested method significantly lowers detection accuracy and decreases false matches in photographs that have been tampered with, increasing the precision of removing the modified region.

In the proposed approach, Each real and matching inliers pack's keypoints are calculated, and a 12x12 neighbourhood is taken into account surrounding them. Both neighbors are subjected to the GLCM approach, and the comparison is determined using these arrays.

LBP and SIFT:

Rather than using the gradient feature that Sift originally involved in creating new descriptors, we use the LBP function and CSLBP function in order to enhance the matching. The NCS and NL descriptors are then combined to create the N(LCS) descriptor. By multiplying the outcomes with weights denoted by powers of two, the LBP code is created. The LBP's grayscale ranges from 0 to 255. We use the notation (P, R), where P is the number of pixels in the immediate area and R is the radius of the circle.

Gabor and SIFT:

The consistency, recollect, and resolution criteria, which are dependent on the number of wrong and accurate matches between two pictures, are used to assess how well these classifiers work. The reliability is calculated by dividing the number of corresponding pairs of points by the typical number of points found across two images[19].

V. Result and Analysis

We took about 30 samples for each class (brittle nails, nails pitting, rough nails, vertical lines on nails) and 5 features in GLCM which form a vector of size 30x5. The training algorithm outperformed in this experiment by classifying the input data.

SIZE=30
BATCH_SIZE=64
TARGET_SIZE=(SIZE,SIZE)
EPOCH_NUM = 140f

1. *Statistical textural feature analysis*

Using GLCM for image processing, the results of image processing employing the GLCM feature are shown in fig. 4. Collection of Local Binary Patterns (LBP) algorithms were created for the background subtraction problem and are available in the LBP Library. Fig-5 shows the application of LBP feature on nail image. Gabor filters have been used to locate and extract text-only sections from complicated document pictures with a variety of frequencies and orientations (both grey and colour). The gabor filter is seen on nail picture in Fig. 6.

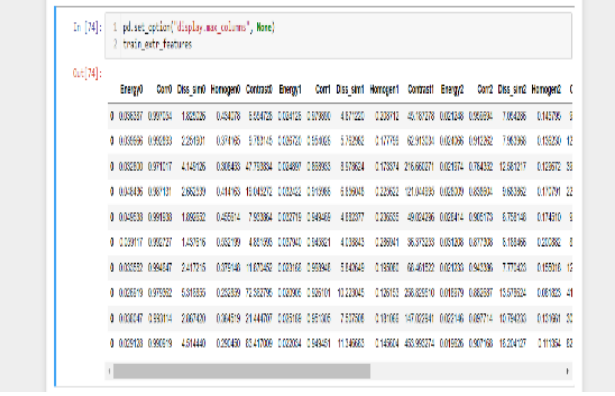


Fig 4-Showing the different GLCM parameters for nail image

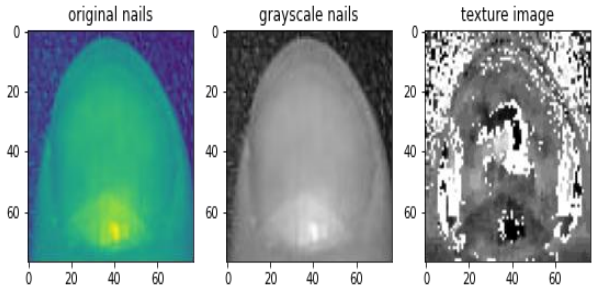


Fig 5-Applying LBP feature on grayscale nail Image

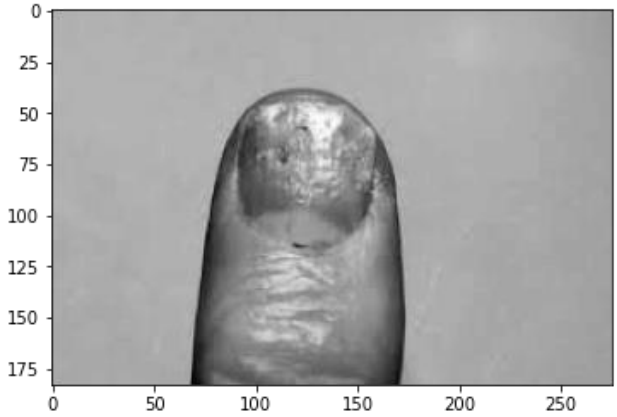


Fig-6 Applying Gabor filter on nail image

For each of the three statistical features (GLCM, LBP, and Gabor filter), Table 4 displays the classi fication accuracy of the testing and training data, while Figures 7 and 8 show the validation accur acy graph and validation loss graph, respectively . The validation and loss graphs for the LBP and Gabor filters, respectively, are shown in Figs. 9 a nd 10, respectively.[20]

Table 4: Algorithm Accuracy for Statistical model Using SVM

Feature	Training Accuracy	Testing Accuracy
GLCM	93.33%	84.24%
Local binary pattern	89.56%	79.32%
Gabor filter	91.50	82.34%

Fig 7-Validation Accuracy Graph for GLCM

fig 8- Validation loss graph for GLCM

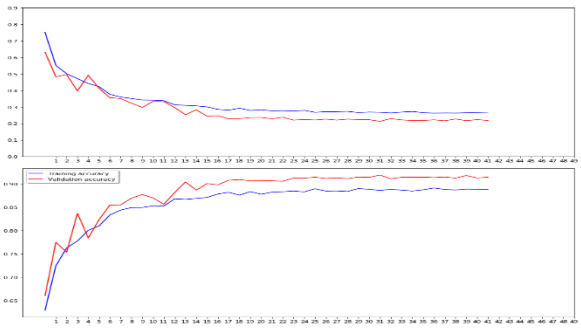


Fig 9-Validation and loss graph for LBP

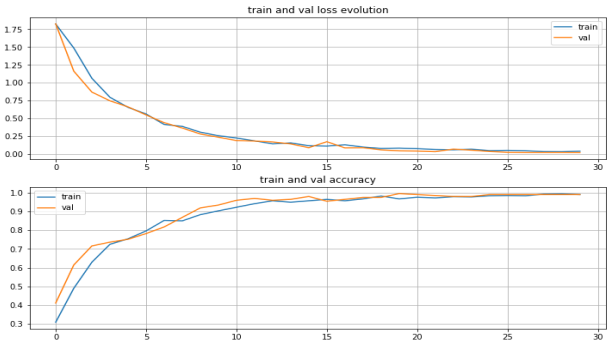


Fig 10-Validation and loss graph for Local Gabor pattern

2. Structural textural feature analysis

Using SIFT for image processing the results of image processing employing the SIFT feature are shown in fig. 12, Fig-13 shows the application of HOG feature on nail image.[21]

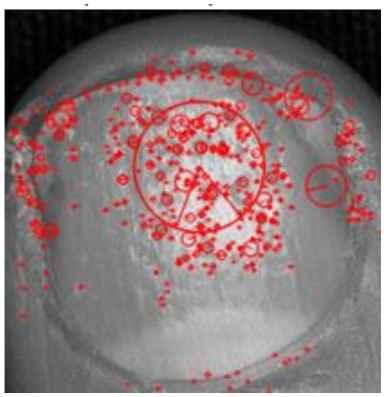


Fig12 – SIFT feature on nail image

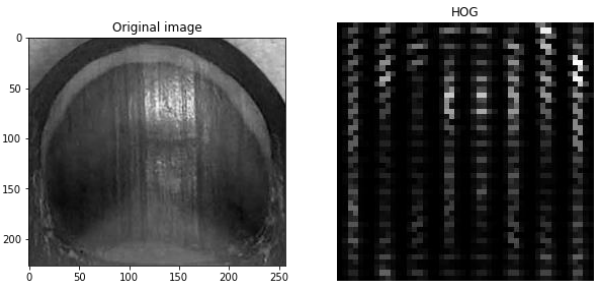


Fig13- HOG feature analysis on nail image

For each of the structural features (SIFT,HOG), T able 5 displays the classification accuracy of the testing and training data, figure 14 show,the vali dation accuracy graph and validation loss graph, respectively. The validation and loss graphs for t he
HOG feature, respectively, is shown in Figs. 15.

Table 5: Algorithm Accuracy for Structural model Using SVM

Feature	Training Accuracy (%)	Testing Accuracy (%)
SIFT	91.50%	83.42%
HOG	86.09%	74.24%

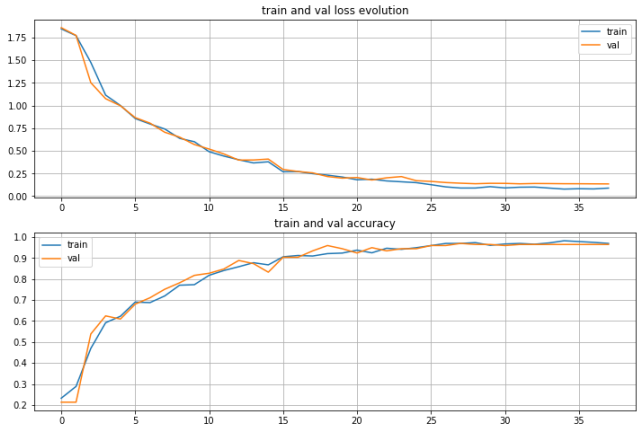


Fig 14-Validation and loss graph for SIFT

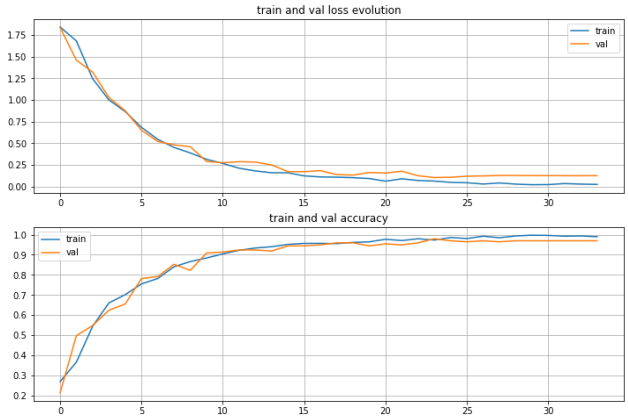


Fig 15-Validation and loss graph for HOG

3. Fusion of Structural and Statistical feature

In this research paper, we analyzed the result of the structural model as well as a statistical model yet to obtain more accurate results we would make a fusion of the most accurate features of the structural and statistical model. [22]

Table 6: Algorithm Accuracy for fusion model Using SVM

Feature	Training Accuracy (%)	Testing Accuracy (%)
GLCM and SIFT	95.36%	92.14%
LBP and SIFT	94.56%	89.33%
Gabor and SIFT	85.65%	77.46%

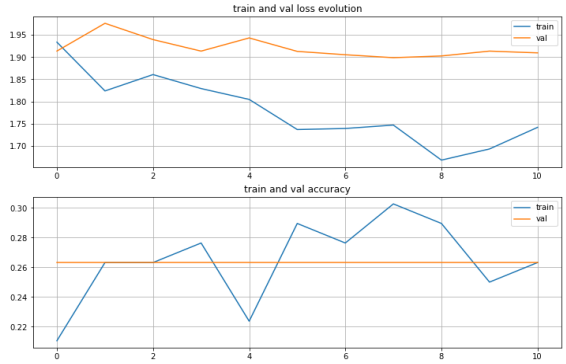


Fig 11-Validation and loss graph for GLCM + SIFT

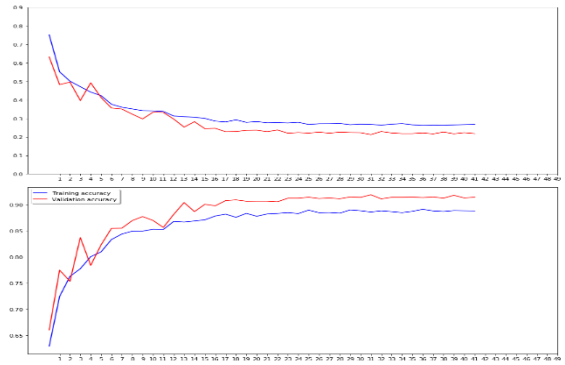


Fig 12-Validation and loss graph for LBP + SIFT

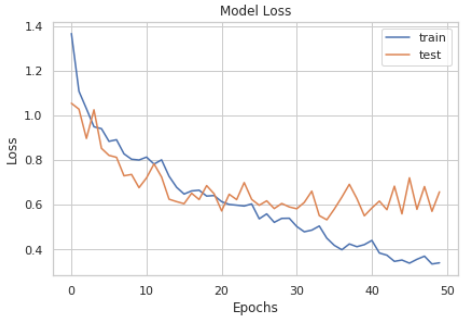


Fig 13-Epoch's loss graph for Gabor filter + SIFT

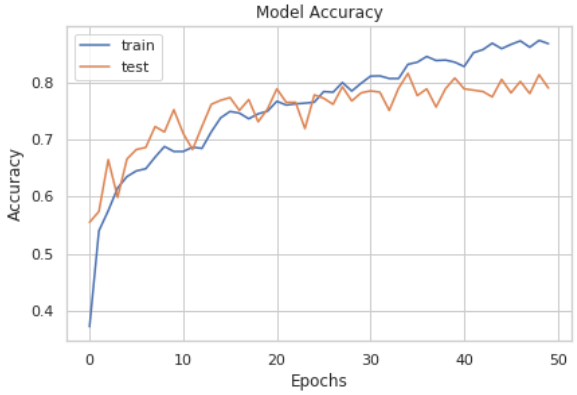


Fig 14-Epochs accuracy for Gabor filter + SIFT

Scale Invariant Feature Transform (SIFT) is a scale-, rotation-, and illumination-invariant feature extraction method. It is also resistant to shifting perspectives. Multiple instances of the same feature can be matched using this approach.[23] In this technique, A similar vector D=d1, d2 .... dn is constructed with each major point, illustrating its ordered Euclidean distances compared to the other SIFT domain classifiers. If the image satisfies the aforementioned cluster condition, RANSAC or Random Sample Consensus [24] is implemented to get precise homography matrix for matched points by subtracting the mean out of each cluster.

The levels of quality of the image have been studied using the Gray-Level Co-occurrence Matrix, or GLCM. The use of this strategy to further hone corresponding areas is the paper's important addition. As a consequence, when GLCM and SIFT are combined, we obtain the most accurate results when compared to other characteristics.

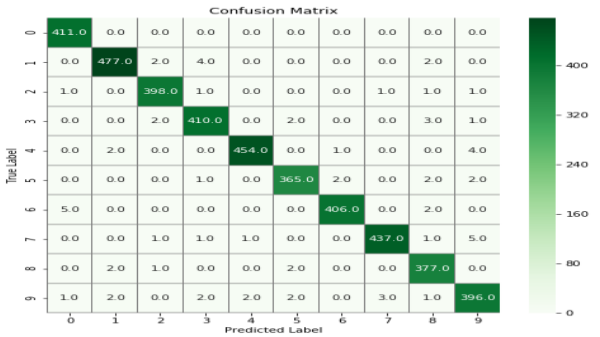


Fig 15-Confusion matrix for GLCM + SIFT feature

The diagonal elements of the confusion matrix show classified groups. Thus, the given confusion matrix gives accurate results for all 4 class

Table 7: comparison of all the accuracies used

Features	Accuracy
GLCM	0.842
LBP	0.793
Gabor	0.823
Hog	0.834
SIFT	0.744
GLCM and SIFT	0.921
LBP and SIFT	0.895
Gabor and SIFT	0.774

VI. CONCLUSION

Here we detect nail disease using a fusion of structural and statistical models. By analyzing the results of different methods we can compare the accuracy of all the models and select the best-suited model for texture analysis from the given table.

The confusion matrix gives the accuracy of the classification problem. 105 images of 4 different classes are classified with a maximum of 92.14% accuracy for the fusion method of GLCM and SIFT feature.

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Brittle Nails	GLCM	Gabor	LBP	SIFT	HOG	GLCM+ SIFT	LBP+ SIFT	Gabor + SIFT	Disease
	0.852	0.798	0.789	0.887	0.654	0.865	0.742	0.658	Pachyonychia Congenita
	0.823	0.802	0.741	0.896	0.742	0.885	0.741	0.554	Terry's Nails
	0.874	0.821	0.743	0.825	0.801	0.921	0.854	0.762	Pachyonychia Congenita
Nail Pitting									
	0.884	0.785	0.698	0.884	0.744	0.896	0.821	0.621	Anonychia
	0.874	0.745	0.623	0.874	0.556	0.917	0.824	0.745	Patella Syndrome
	0.841	0.761	0.641	0.874	0.658	0.908	0.761	0.665	Patella Syndrome
Vertical Lines on Nail									

	0.873	0.732	0.698	0.845	0.632	0.895	0.798	0.704	Lunular Dyschromia
	0.845	0.789	0.662	0.874	0.711	0.887	0.703	0.684	Loss of Lunula
	0.874	0.823	0.766	0.798	0.698	0.895	0.774	0.654	Splinter Hemorrhage
Rough/Broken Nails									
	0.895	0.742	0.771	0.772	0.712	0.894	0.725	0.654	onycholysis
	0.845	0.765	0.796	0.811	0.698	0.845	0.774	0.668	onycholysis
	0.778	0.733	0.623	0.695	0.554	0.787	0.711	0.541	Splinter Hemorrhage