Early Disease Detection Through Nail Image Processing Based on Ensemble of Classifier Models

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Abstract— Medical science has progressed in many ways and different methods have been developed for the diagnosis of diseases in the human body and one of the ways to identify the diseases is through the close examination of nails of the human palm. The main aim of this study is to compare the performance of various classifier models that are used for the prediction of various diseases. The Performance analysis is done by applying image processing, different data mining and machine learning techniques to the extracted nail image through our proposed system which does nail analysis using a combination of 13 features (Nail Color, Shape and Texture) extracted from the nail image. In this paper we have compared different machine learning classifiers like Support Vector Machine, Multiclass SVM and K-Nearest Neighbor through ensemble of these classifiers with different features so as to classify patients with different diseases like Psoriasis, Red Lunula, Beau's Lines, Clubbing, etc. These approaches were tested with data images from Hospitals and workplaces. The performance of the different classifiers have been measured in terms of Accuracy, Sensitivity and Specificity.

Keywords-*Machine Learning, SVM, Muti-class SVM, KNN, Nail Image Processing*

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I. INTRODUCTION

In a human being, various systemic and dermatological diseases can be easily diagnosed through careful examination of nails of both hand and legs. A lot of nail diseases have been found to be early signs of various underlying systemic diseases [1]-[7]. The color, texture or shape changes in nails are symptoms of various diseases primarily affecting nails. And if we are able to use digital image processing techniques for detecting such changes in the human nail, then we would be able to get more accurate results and predict various diseases easily.

A nail disorder is a condition caused by injury to the nail or due to some diseases or imbalances in the body.

Nail Disorders can be classified into four categories – Congenital, Traumatic, Infectious, Tumors[8]-13]. The various diseases are:

a. Congenital: Anonychia, Nail Patella Syndrome, Pachyonychia congenital
b. Traumatic: Onychophagia, Hangnail, Onychog- ryphosis, Onychocryptosis
c. Infectious: Paronychia, Pseudomonas infection
d. Tumors: Glomus tumor, Melanocytic nevi

Nail Abnormalities can also be classified into following three categories based on changes in shape [1][8], surface[10] and color of the nails. They are:

a. Shape Changes: Clubbing, Koilonychia, Onycholysis
b. Surface Changes: Beau's Lines, Meuhrcke's Line, Leukonychia
c. Color Changes: Terry's nails, Yellow nail syndro-me, Lindsay's nails, Red Lunula, Splinter Hemor-rhages

There are various testing techniques for diagnosis of disease which are followed by medical practitioners using pathological tests as basis. Mostly these test involves taking blood samples which are quite painful and require the presence of the patient. In our proposed system, Nail Image Processing System (NIPS), we have focused on image recognition based on combination of features of nail like color, shape and texture. In the field of healthcare, study of human nail has its own significance. Many diseases can be diagnosed by scrutinizing nails of the hand. As human eyes have limitation to scrutinize texture and distinction in color. This paper also involves an algorithm which will automatically extract nail area and scrutinize this nail part for disease detection based on a combination of nail color, shape and texture features of nail. The pathological tests are cumbersome to perform as their results can vary and these tests can take more than 24 hours by the examiner to establish name of the disease. Moreover, it requires the patient to be present for test, but the nail image processing system requires only the image of patient's hand that can be obtained easily and it is not cumbersome to perform [14][15].

Supervised or machine learning is a multidisciplinary field of study which is mainly concerned with the design of algorithms which will allow the computers to learn. In machine or supervised learning, classification, is a task of identifying, to which class the new observation belongs. An algorithm which implements the classification is mainly called as the classifier.

Data mining is one of the "Knowledge Discovery in Databases" processes. The main aim of the data mining process is to extract information from a data set and transform it into an understandable structure for further use. Data mining has become the mostly used activity in all areas of medical science research. Data mining problems are often solved using different approaches from both computer sciences, such as multi-dimensional databases, machine learning, soft computing and data visualization; and statistics, including hypothesis testing, clustering, classification, and regression techniques. In recent years, data mining has been used widely in the areas of science and engineering, such as bioinformatics, genetics, medicine, and education.

In our proposed system, Nail Image Processing System (NIPS), a total of 13 features of the human nail are extracted and then they are ensemble with three classifiers-SVM, Multi-class SVM and KNN which is then used for disease prediction. The input to the system is the backside of the palm which is captured using a camera. Then the Region of Interest, the nail area is segmented automatically. The segmented nail area is then processed for extracting the features of nail like nail color, shape and texture. The extracted features are then taken together to form a feature vector which is used for comparing with the existing datasets and the diseases are predicted using the knowledge base [16]. Thus the system will assist us in detecting various diseases in their early stage itself easily without spending much of our time and money.

II. PROPOSED SYSTEM

The input to the proposed system is the backside of the palm on a white background. Then, from the palm image, the Region of Interest (ROI), the nail region is extracted using Canny's edge detection

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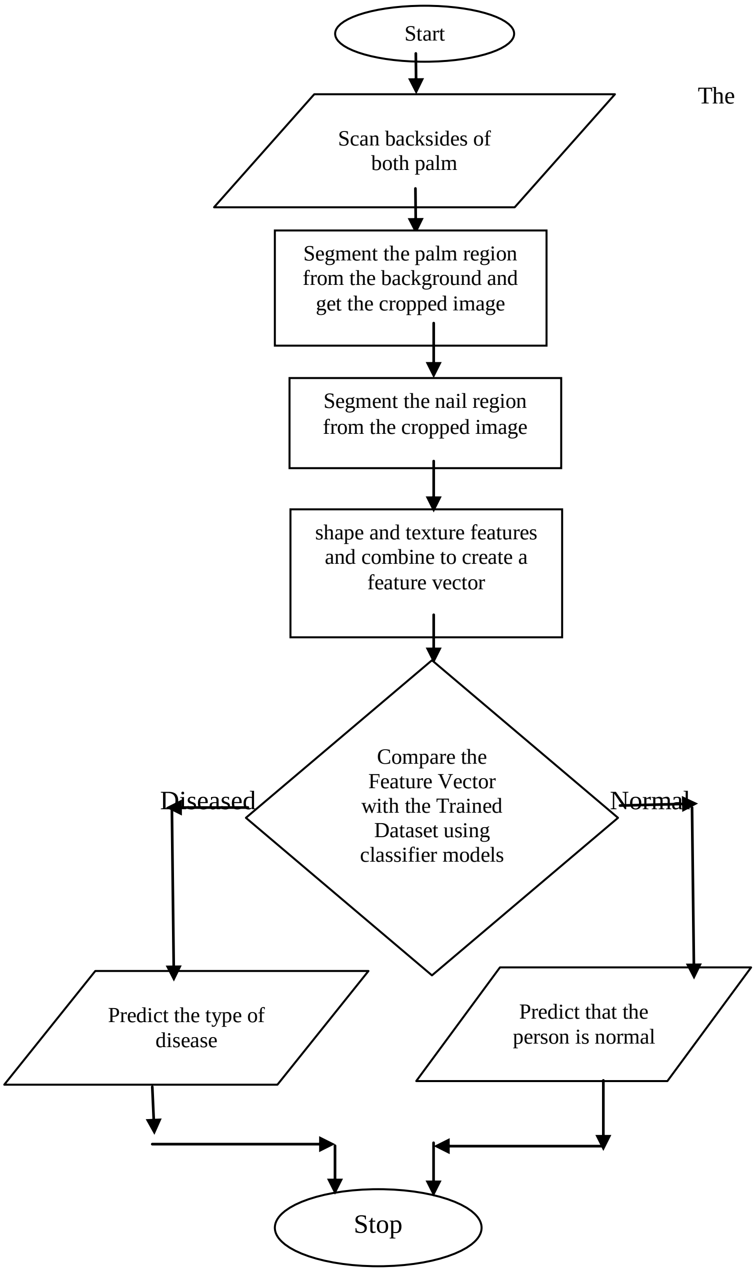
method and segmentation process. Then the nail color, shape and texture are extracted to form a feature vector which is then compared with the existing database of diseased and normal nail. The proposed system uses a Ensemble-Classification Method for classification and prediction of diseases [17].

A. *Block Diagram of the Proposed Model*



The

Fig 1: Flow Chart for NIPS

III. METHODOLOGY OF THE PROPOSED SYSTEM

A. *Scanning back sides of both palms*

The back sides of both the left and right palms are scanned using a good camera with proper light. The palm has to be placed on a white background with minimum distance between the fingers. The fingers should not be nail-polished.

B. *Palm region extracted from the background*

The palm can be segmented manually and automatically from the background image using the imcrop ( ) function in MATLAB. As we make use of the skin color, it is invariant to scaling or rotation. And then after the palm region is segmented , all the other pixels of the background is set to the same color, so that it does not cause any confusions for further processing and finally the palm is cropped.

C. Segmentation of Nail region and Extraction of Features of Nail like Color, Shape and Texture

Nail regions are segmented, and various features of the nail like color, shape and texture are extracted and recorded together to form a feature vector[18]-[21]. In the proposed system, NIPS, 13 features of nail color, shape and texture were extracted to form a feature vector. The various features are as follows:

a) Color features : Mean/Median
Standard Deviation
Skewness
Kurtosis

b) Shape features : Area
Perimeter
Compactness
Eccentricity

c) Texture features: Energy
Entropy
Contrast
Correlation
Homogenity

D. *Disease Prediction*

The extracted features which are stored in a vector are compared with the existing trained dataset and the diseases are predicted using the ensemble-classification method.

IV. CLASSIFIER MODELS FOR DISEASE PREDICTION

Classification of images generally involves two main tasks:

a. Feature extraction
b. Classification

During Classification, three patterns are recognized:

a. Binary
b. Multi-class
c. Multi-label

In the case of Binary pattern, it classifies images into exactly two predefined classes-positive or negative [22]. In multi-class pattern, an image belongs to exactly one class from a set of 'm' classes [23]. In multi-label pattern, an image belongs to several classes at the same time, i.e. overlapping of classes may occur [24]. The Binary pattern has been set as a base pattern from which the other two patterns-multi-class and multi-label are designed. In our proposed, ensemble-classification model, we have used multi-label pattern for identification of various diseases.

Ensemble-classifier model provides extra degree of freedom in the classical bias / variance tradeoff, permitting resolution that would be very much complex to reach with only a single classifier. Because of these advantages, ensemble classification model has been applied to many tedious real-world problems. A general mode of ensemble-classification is illustrated in Figure 2

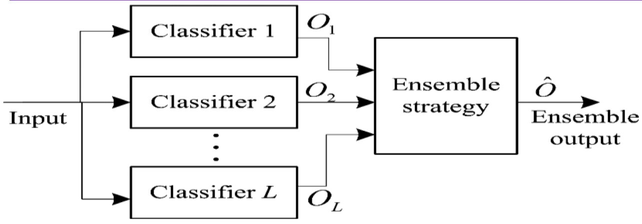


Fig 2: Ensemble Classifier Model
[Courtesy: http://opticalengineering.spiedigitallibrary.org/article.aspx?articleid=1352706]

In the proposed model, color, shape and texture features are considered and ensemble-classification process [25] is carried out for disease detection. Here we have used three classifiers namely SVM, Multi-class SVM and KNN for the ensemble process. All the classifiers are modeled to work as multi-label image classifier, and the performance measurements like Sensitivity, Specificity and Accuracy are found using the ensemble classifiers for the image feature vector sets. The classifiers proposed under each of the categories are:

a. Single Classifier-Single Feature Model
   - SVM with Texture Features (1T)
   - MSVM with Texture Features (2T)
   - KNN with Texture Features (3T)
   - SVM with Color Features (1C)
   - MSVM with Color Features (2C)
   - KNN with Color Features (3C)
   - SVM with Shape Features (1S)
   - MSVM with Shape Features (2S)
   - KNN with Shape Features (3S)

b. Single Classifier-Multiple Feature Model
   - SVM with Color and Shape Features (1CS)
   - SVM with Shape and Texture Features (1ST)
   - SVM with Color and Texture Features (1CT)
   - MSVM with Color and Shape Features (2CS)
   - MSVM with Shape and Texture Features (2ST)
   - MSVM with Color and Texture Features (2CT)
   - KNN with Color and Shape Features (3CS)
   - KNN with Shape and Texture Features (3ST)
   - KNN with Color and Texture Features (3CT)
   - SVM with Color, Shape and Texture Features (1CST)
   - MSVM with Color, Shape and Texture Features (2CST)
   - KNN with Color, Shape and Texture Features (3CST)

c. Multiple Classifier-Single Feature Model
   - SVM and MSVM with Texture Features (12T)
   - MSVM and KNN with Texture Features (23T)
   - SVM and KNN with Texture Features (13T)
   - SVM and MSVM with Color Features (12C)
   - MSVM and KNN with Color Features (23C)
   - SVM and KNN with Color Features (13C)
   - SVM and MSVM with Shape Features (12S)
   - MSVM and KNN with Shape Features (23S)
   - SVM and KNN with Shape Features (13S)
   - SVM,MSVM,KNN with Color Features(123C)
   - SVM,MSVM,KNN with Shape Features(123S)
   - SVM,MSVM,KNN with Texture Features(123T)
   -

d. Multiple Classifier-Multiple Feature Model
   - SVM and MSVM with Color, Shape Features (12CS)
   - SVM and MSVM with Shape, Texture Features (12ST)
   - SVM and MSVM with Color, Texture Features (12CT)
   - SVM and MSVM with Color, Shape and Texture Features (12CST)
   - MSVM and KNN with Color, shape Features (23CS)
   - MSVM and KNN with shape, texture Features (23ST)
   - MSVM and KNN with Color, texture Features (23CT)
   - MSVM and KNN with Color, Shape and Texture Features (23CST)
   - SVM and KNN with Color, Shape Features(13CS)
   - SVM and KNN with Shape, Texture Features (13ST)
   - SVM and KNN with Color, Texture Features (13CT)
   - SVM and KNN with Color, Shape and Texture Features (13CST)
   - SVM,MSVM and KNN with Color, Shape and Texture Features (123CST)

Thus 46 Classifier models are developed. All the models involve three steps:

1. All the classifiers are trained with the training feature vector
2. Then the selected classifiers will be used to classify the test feature vector to its corresponding output label
3. Then using the aggregation method of majority voting scheme, the individual results are merged and the final decision is taken.

The accuracy of the proposed ensemble-classification model depends on the following properties.

A. Number and Type of classifiers used
B. The different image features used by the classifiers.
C. Technique used during ensemble classification
D. The aggregation method used
E. Type of training that is given to the model

A. Number and Type of Classifier

In the proposed model, the classifier models that have been used for the prediction of various diseases through nail analysis are:

(i) Support Vector Machine(SVM)
(ii) Multiclass SVM
(iii) K-Nearest Neighbor(KNN)

(i) Support Vector Machine(SVM)

In machine learning, SVM is a supervised learning method which gives machines the ability to learn without being explicitly programmed. The idea of support vector machine is to create a hyper plane in between data sets to indicate which class it belongs to. The challenge is to train the machine to understand structure from data and mapping with the right class label, for the best result, the hyper plane has the largest distance to the nearest training data points of any class.

A classification task usually involves training and testing data which consist of some data instances. Each instance in the training set contains a target value and several other attributes. The aim of SVM is to produce a model which will predict the target value of data instances in the testing set. SVM classification involves the identification of datasets which are closely connected to the known classes [26][27]. This is called feature selection or feature extraction. Feature selection and SVM classification are used for predicting unknown samples. They can be used to identify key sets which are involved in all the processes which distinguish the different classes.

A multi-class classification task usually involves separating data into training set and testing set. Each instance in the training set includes one "target value", (i.e., class labels) and several "attributes" (i.e., features). The objective of SVM is to create a model (based on the training data) which predicts the target values of the test data given only the test data attributes [28].

(ii) Multiclass SVM

Support vector machine (SVM) originally separates the binary classes (k = 2) with a maximized margin. However, real-world problems often require the discrimination for more than two categories. Thus, the multi-class pattern recognition can be used. The multi-class classification problems (k > 2) are commonly decomposed into a series of binary problems such that the standard SVM can be directly applied. Two representative ensemble schemes are one-versus-rest (1VR) [29] and one-versus-one (1V1) [30] approaches.

Multiclass SVM models combines multiple binary-class optimization problems into one single objective function and simultaneously achieves classification of multiple classes. The one-versus-rest (1VR) approach [29] constructs k separate binary classifiers for k-class classification. The m-th binary classifier is trained using the data from the m-th class as positive examples and the remaining k − 1 classes as negative examples. During the test, the class label is determined by the binary classifier that gives maximum output value. Another classical approach for multi-class classification is the one-versus-one (1V1) or pairwise decomposition [31]. It evaluates all possible pairwise classifiers and thus induces k (k − 1)/2 individual binary classifiers. Applying each classifier to a test example would give one vote to the winning class. A test example is labeled to the class with the most votes.

In this paper, the extracted features which are stored in a vector are compared with the existing trained dataset and the diseases are predicted using the Multiclass SVM classification method. In the Multiclass SVM method, the one-versus-rest approach is used. Here we have used classes for different diseases and one class for healthy nails. In the proposed model binary classifiers were trained up, for example, Darier's versus not-Dariers, Psoriasis versus not-Psoriasis, Beau's Lines versus not-Beau's Lines,……………., Healthy versus not-Healthy. Then, either the positive class that's "best" (e.g., furthest from the margin across all 25 runs) is selected. Or if none of the classifications are positive (i.e., they're all not-X), the "opposite" of class that's worst (e.g., closest to the margin) is selected.

(iii) K-Nearest Neighbor

K-Nearest Neighbor (KNN) is a very simple, highly efficient and effective algorithm for pattern recognition. In KNN, samples are classified based on the class of their nearest neighbor.

K-nearest neighbor algorithm is a technique for classifying data based on the closest training examples in the feature space.

The algorithm for KNN classifier is as follows:

a. First the dataset is divided into a testing set and training set.
b. For each row in the testing set, the "K" nearest training set objects is found, and the classification of test data is determined by majority vote with ties are broken at random. If there are ties for the K^{th} nearest vector then all the instances are included in the vote [32].
c. Calculating the distances between the testing data vector and all of the training vectors using a particular distance calculation methodology which is given as follows: Considering the case of two input variable; the Euclidean distance between two input vectors p and q is computed as the magnitude of difference in vectors i.e. p - q, Where both the data are having "m" dimensions i.e. p= (p_1, p_2… p_m) and q= (q_1, q_2,…,q_m).

The Euclidean distance between "p" and "q" is found to be:

$$D(p,q) = |p-q|$$
$$= \sqrt{(p_1-q_1)^2+(p_2-q_2)^2+\ldots+(p_m-q_m)^2}$$

d. Then take the test instance "x" and find the K-nearest neighbors in the training data
e. Assign "x" to the class occurring with the most among the K neighbors.

In this paper, we have used the following steps for the KNN Classifier model:

a. A training set is prepared which contains the features of 25 different diseased and healthy nails. The images of different diseased and healthy nails were also given for the training set to the MATLAB function KNNClassification.fit( ).

b. Then, a testset was prepared which contained the 13 features of the image to be tested

c. The Trainedset and Testset was given to the function predict( ) for prediction of various diseases belonging to 25 different classes[1 2 3 4 …….25].

B. Nail Image Features

In this research study, we have extracted 13 features from the 483 images of diseased and healthy nails. The various features extracted are categorized as:

a. Color features : Mean/Median
   Standard Deviation
   Skewness
   Kurtosis
b. Shape features : Area
   Perimeter
   Compactness
   Eccentricity
c. Texture features: Energy
   Entropy
   Contrast
   Correlation
   Homogenity

The Nail regions are segmented, and various features of the nail like **color, shape and texture** are extracted and recorded. A mix of **Histogram** and **Statistical based feature extraction method** for extracting the Color feature is used as it has high accuracy [33][34][35] . Histogram is used as a model of probability distribution of intensity level and Statistical features provide information about the characteristics of intensity level distribution for the image. The various

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statistical features used are **Mean or Median, Standard Deviation, Skewness and Kurtosis**.

Table I presents the equations for calculating the mean, standard deviation, kurtosis and skewness of the color channels, where M and N denotes the dimension and total number of pixels in the image, P_{ij} denotes the color value of i^{th} column and j^{th} row.

TABLE I: COlOR FEATURES

Si.No	Feature Name	Feature Calculation
1	Mean	$\mu = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} P_{ij}$
2	Standard Deviation	$\sigma = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(P_{ij}-\mu)^2}$
3	Skewness	$\theta = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(P_{ij}-\mu)^3}{MN\sigma^3}$
4	Kurtosis	$\gamma = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(P_{ij}-\mu)^4}{MN\sigma^4}$

Besides the color features, **shape features** also provide useful information for retrieval of information about images. The shape of an object is a binary image representing the extent of the object. Shape features can be categorized as boundary-based and region-based. The former extracts features based on the outer boundary of the region while the latter extracts features based on the entire region [36]. Feature vectors extracted from boundary-based representations provide a richer description of the shape and for this reason, boundary based shape features are extracted from the various regions of an image. Features like **area, perimeter, compactness, eccentricity** are extracted.

TABLE II: SHAPE FEATURES

Si.No	Feature Name	Feature Calculation
1	Area	It is the number of pixels in the region described by the shape. It is measured as the count of the internal pixels
2	Perimeter	It is the number of pixels in the boundary of the shape
3	Compactness	It is a measure of how closely packed is the shape. $\text{Compactness} = \frac{(\text{region border length})^2}{\text{area}}$
4	Eccentricity (Roundness)	It is the ratio of the longest chord of a shaped object to longest chord perpendicular to it. Eccentricity is a measure of how circular a shape is.

Another important feature that has been proved to be important and useful in the area of computer vision and image analysis is **Texture**. An image texture feature is a set of metrics calculated to provide information about the spatial arrangement of color or intensities in an image or selected region of an image [37]. Texture features can be extracted using either statistical approaches or transformation approaches. Statistical approaches can be divided into two areas which are the spatial domain approach and the frequency domain approach. The spatial domain approach, are more powerful than frequency domain approach. One of the most widely used approaches to texture analysis, the Gray Level Co-occurrence Matrix (GLCM) approach. The proposed system has used 14 texture features that utilize the spatial relationship amongst gray level values of pixels with in a region.

The GLCM is a tabulation of how often different combinations of pixel brightness values (grey levels) occur in an image. Various texture features like entropy, energy, contrast, homogeneity and correlation are extracted from each sub band. And various Tamura features like coarseness, contrast, directionality, line-likeness, regularity and roughness are also extracted from each sub band. These texture features are calculated as shown in Table III, where P_{ij} is the probabilities calculated for values in GLCM and N is the size of GLCM.

TABLE III: TEXTURE FEATURES

Si.No	Feature Name	Feature Calculation
1	Entropy	$\sum_{i,j=0}^{N-1} P_{i,j}(-\ln P_{i,j})$
2	Energy	$\sqrt{\sum_{i,j=0}^{N-1} P_{i,j}^2}$
3	Contrast	$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2$
4	Homogeneity	$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}$
5	Correlation	$f = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} p_{d,\theta}(i,j)\frac{(i-\mu_x)(j-\mu_y)}{\sigma_x\sigma_y}$

Coarseness has a direct relationship to scale and repetition rates and an image will contain textures at several scales. Coarseness aims to identify the largest size at which a texture exists, even where a smaller micro texture exists. Contrast aims to capture the dynamic range of grey levels in an image, together with the polarization of the distribution of black and white. Degree of Directionality is a global property over a region. The feature described does not aim to differentiate between different orientations or patterns, but measures the total degree of directionality. It is measured using the frequency distribution of oriented local edges against their directional angles.

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C. Technique Used During Ensemble Classification

In this step, we decide the specific method that can be used for partitioning the dataset and aggregation of results.

A machine-learning algorithm learns to find patterns in the input that is fed to it. This input is referred to as **training data**. And once a machine learning algorithm learns the underlying patterns of the training data, it needs to be tested on fresh data (or **test data**) that it has never seen before, but which still belongs to the same distribution as the training data. If our machine learning algorithm performs well on the test data then it is considered as a machine learning model that generalizes our dataset of interest. Thus, it becomes very important to have a separate data set to train and test a classifier. Several methods exist, like Holdout method, Cross-validation method, Bootstrap Forest method, Re-substitution method [38].

The proposed ensemble-classifier model uses the Holdout method for separating the dataset into Training and Testing datasets. Here, we have used two-thirds of the data as Training Dataset and the remaining one-third as the Testing Dataset.

D. Aggregation Method

While using multiple classifiers, a method is needed which will combine the result of various classifiers. Nine such combination methods like Majority voting, Maximum, Sum, Min, Average, Product, Bayes, Decision Template and Dempster-Shafer methods can be applied in the ensemble model for creating the feature subsets. For ensembling, we need to generate a pool of classifiers by combining trained classifiers using different combination methods [39].

This research work uses **Majority Voting Scheme** as the aggregation algorithm during ensembling. Majority voting scheme is one of the oldest strategies and it is used because of its speed and simplicity. The method is explained as below:

Let D = (D1, D2, . . . , Dn) be a set of classifiers,
Di : Rk → Ω (i = 1, . . . , n) where Ω = (ω1, ω2, . . . , ωc) is a set of class labels. If the classifier decisions are combined in the majority voting, then the class label ωi is assigned to x that is supported by the majority of the classifiers Di. In the case of a tie, the decision is usually made randomly.

As a special case, we can consider binary classifiers examined exhaustively in the literature. Let n(n ∈ N) be odd, Ω = (ω1, ω2) (that is, each classifier output is a binary vector) and all classifiers have the same classification accuracy p(p ∈ [0, 1]). An accurate class label is given by the majority vote if at least [n/2] classifiers give correct answers. The overall accuracy of correct classification in majority voting with independent classifier decisions can be computed by the binomial formula:

$$P = \sum_{k=0}^{\lfloor n/2 \rfloor} \binom{n}{k} p^{n-k}(1-p)^{k}.$$

E. Types of Training

The various methods used while training a multiple classifier system are:

a) Training of the individual classifiers and then applying aggregation which does not require further training.
b) Training of the individual classifiers and then followed by training of the aggregation
c) Simultaneous training of the whole scheme

This research uses the first method where training of the individual classifiers are done and then further training of the aggregation is not required. This method is selected because the ensemble classification method depends on the output of the individual classifiers.

V. EVALUATION MEASURES

The performance analysis was done using the statistical measures for Classification like Sensitivity, Specificity and Accuracy. For calculating these criteria we have used the confusion matrix in our calculation process [31]. The general view of confusion matrix is as given below in Table IV.

TABLE IV: CONFUSION MATRIX

	Predicted Class		
		Yes	No
Actual Class	Yes	True Positive	False Negative
	No	False Positive	True Negative

In the confusion matrix the predicted class is the class that is predicted by the classifier and the actual class is the class that is given in the data set.

Sensitivity measures how well a particular test predicts one category from another. Specificity measures how well a particular test predicts the other category and Accuracy measures how well the test predicts both the categories. From the Confusion matrix the sensitivity, specificity and accuracy are measured as given below:

$$\text{Sensitivity} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$\text{Specificity} = \frac{True\ Negative}{True\ Negative + False\ Positive}$$

$$\text{Accuracy} = \frac{True\ Positive + True\ Negative}{True\ Positive + False\ Positive + True\ Negative + False\ Negative}$$

Here,
True Positive - means the total number of diseased images correctly identified by the algorithm
True Negative - means the total number of diseased images mistakenly identified by the algorithm
False Positive - means the total number of diseased images correctly rejected by the algorithm

False Negative - means the total number of diseased images mistakenly rejected by the algorithm

VI. TESTCASES

The proposed system was tested with 483 image samples of palm of 40 persons which were captured using a digital camera. The photos were taken from hospitals and workplaces. Five images per person were taken. Some of the nail images and their outputs are shown in Table III. Out of the 483 image samples, 15 samples each of 24 diseases and 123 samples of healthy persons were taken. For the TrainingSet, 13 Features of 24 diseases and normal nail were used. And out of the total 360 diseased images, 240 images were used for training and 120 images were used for TestSet. From the samples of healthy nail, 86 images were used for TrainingSet and 41 images were used for TestSet.

The dataset has 13 features extracted and 25 predicted classes. The features are as follows:

a) Color features : Mean/Median
Standard Deviation
Skewness
Kurtosis

b) Shape features : Area
Perimeter
Compactness
Eccentricity

c) Texture features : Energy
Entropy
Contrast
Correlation
Homogenity

The 25 predicted classes [1 2 3 4 ……25] are as follows:

Class 1 : Healthy Nail
Class 2 : Dariers Disease
Class 3 : Psoriasis Disease
Class 4 : Beau Lines Disease
Class 5 : Eczema Disease
Class 6 : Lindsays Disease
Class 7 : Melanonychia Disease
Class 8 : Muehrckes Lines Disease
Class 9 : Nail Patella Disease
Class 10 : Onchocryptosis Disease
Class 11 : Onchophagia Disease
Class 12 : Pachyonychia Disease
Class 13 : Terry's Nail Disease
Class 14 : Alopecia Areata Disease
Class 15 : Anonychia Disease
Class 16 : Clubbing Disease
Class 17 : Glomustumor Disease
Class 18 : Hang Nail Disease
Class 19 : Koilonychia Disease
Class 20 : Leukonychia Disease
Class 21 : Paronychia Disease
Class 22 : Pseudomonas Disease
Class 23 : Red Lunula Disease
Class 24 : Splinter Hemorrhage Disease
Class 25 : Yellow Nail Disease

The tool that we have used for our experiment is Matrix Laboratory (MATLAB 2013a) in Windows 7 and our results are compared in it.

VII. RESULTS AND DISCUSSIONS

In this research, we have used 3 classifier techniques- SVM, Multiclass SVM and KNN for the prediction of various diseases through the analysis of human nail images. In SVM Classifier, we have used linear kernel as the kernel function and in KNN, we have used k=5, because it gives the highest performance measure. Experiments were conducted based on the hold-out method. The average results were taken as the final outcome of all the classifiers. The results of various ensemble classifiers are presented below. Here the comparison was done so as to find out which combination of classifiers and features are the best for the prediction of various diseases through the analysis of nail images.

A. Single Classifier-Single Feature Model

Single Classifier-Single Feature ensemble classification model has produced nine classifier models namely 1T, 2T, 3T, 1C, 2C, 3C, 1S, 2S and 3S. Sensitivity, Specificity and Accuracy were measured and the results were tabulated and are shown in Table V.

From the result we can clearly understand that the performance measure of the KNN classifier combined with texture, color and shape features produces the best result followed by Multiclass SVM. Moreover, it is also evident that texture feature has better result than color and shape features in the case of all classifiers.

TABLE V: COMPARISON RESULT OF THE SINGLE CLASSIFIER-SINGLE FEATURE MODEL

COMPARISION RESULTS			
Classifier Technique	**SPECIFICITY**	**SENSITIVITY**	**ACCURACY**
1T	64.8	81.54	84.78
2T	65.5	78.23	87.34
3T	**74.19**	**85.6**	**94.45**
1C	68.4	75.56	84.53
2C	69.23	76.67	86.56
3C	72.5	84.32	92.13
1S	61.7	68.5	78.56
2S	68.2	73.1	84.34
3S	71.65	83.12	90.18

T-Texture feature, C-Color Feature, S-Shape Feature
1-SVM Classifier, 2-Multiclass SVM Classifier, 3-KNN Classifier

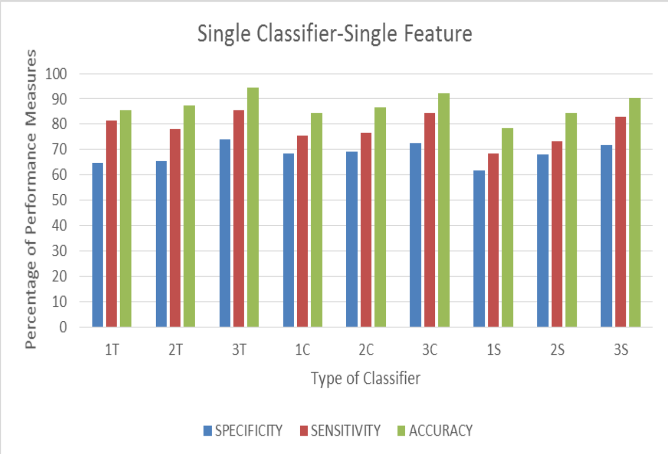

Fig 3: Performance Analysis of Single Classifier-Single Feature Model

B. Single Classifier-Multiple Feature Model

Single Classifier-Multiple Feature ensemble classification model has produced twelve classifier models namely 1CS, 1ST, 1CT, 2CS, 2ST, 2CT, 3CS, 3ST, 3CT, 1CST, 2CST and 3CST. Sensitivity, Specificity and Accuracy were measured and the results were tabulated and are shown in Table VI

From the result we can clearly understand that the performance measure of the KNN classifier when combined with all the three features texture, color and shape produces the best result than one or two feature combination. KNN is then followed by Multiclass SVM. Moreover, it is also evident that the three feature combination has better result than one or two feature combination with classifier.

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TABLE VI: COMPARISON RESULT OF THE SINGLE CLASSIFIER-MULTIPLE FEATURE MODEL

COMPARISION RESULTS			
Classifier Technique	SPECIFICITY	SENSITIVITY	ACCURACY
1CS	63.12	72.78	79.23
1ST	64.3	78.2	82.7
1CT	67.8	85.3	85.2
2CS	65.23	79.34	84.12
2ST	67.35	80.23	85.3
2CT	68.12	82.56	88.8
3CS	65.1	81.78	89.45
3ST	75.32	86.34	92.13
3CT	78.32	88.45	96.23
1CST	73.35	92.63	85.49
2CST	75.92	97.5	89.93
3CST	**88.76**	**98.35**	**97.56**

T-Texture feature, C-Color Feature, S-Shape Feature
1-SVM Classifier, 2-Multiclass SVM Classifier, 3-KNN Classifier

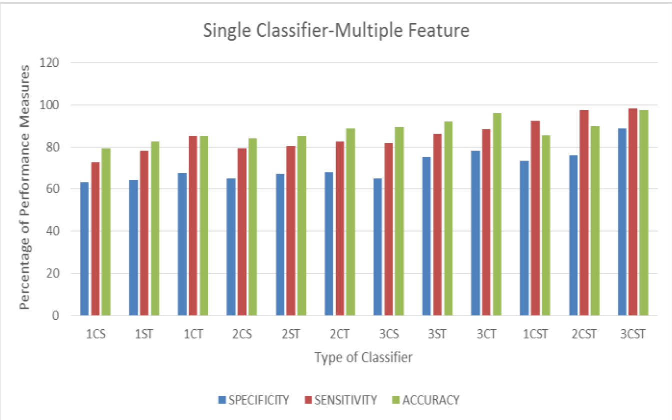

Fig 4: Performance Analysis of Single Classifier-Multiple Feature Model

C. *Multiple Classifier-Single Feature Model*

Multiple Classifier-Multiple Feature ensemble classification model produces twelve classifier models namely 12T, 23T, 13T, 12C, 23C, 13C, 12S, 23S, 13S, 123C, 123S and 123T. Sensitivity, Specificity and Accuracy were measured and the results were tabulated and are shown in Table VII.

From the result we can understand that the performance measure of the Multiclass SVM and KNN classifier when combined with all the texture feature produces the best result. It is then followed by SVM and KNN Classifier combined with texture feature. Moreover, it is also evident that the three classifier combination has a poor result than one or two classifier combination with individual features.

TABLE VII: COMPARISON RESULT OF THE MULTIPLE CLASSIFIER-SINGLE FEATURE MODEL

COMPARISION RESULTS			
Classifier Technique	SPECIFICITY	SENSITIVITY	ACCURACY
12T	84.2	92.1	92.34
23T	**89.12**	**99.23**	**98.75**
13T	87.67	95.19	96.76
12C	79.42	93.6	90.38
23C	83.8	96.3	95.89
13C	80.1	94.12	92.11
12S	72.24	90.66	89.45
23S	76.34	94.8	94.1
13S	74.6	92.56	91.4
123C	68.34	84.68	84.1
123S	65.9	83.4	83.5
123T	70.2	89.1	86.23

T-Texture feature, C-Color Feature, S-Shape Feature
1-SVM Classifier, 2-Multiclass SVM Classifier, 3-KNN Classifier

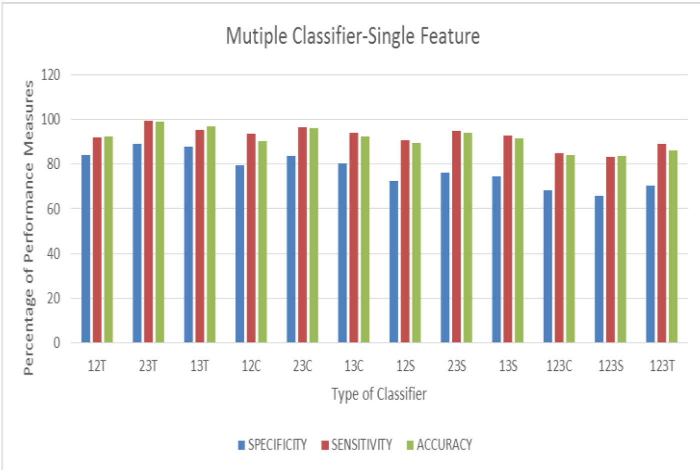

Fig 5: Performance Analysis of Multiple Classifier-Single Feature Model

D. *Multiple Classifier-Multiple Feature Model*

Multiple Classifier-Multiple Feature ensemble classification model produces thirteen classifier models namely 12CS, 12ST, 12CT, 12CST, 23CS, 23ST, 23CT, 23CST, 13CS, 13ST, 13CT, 13CST, 123CST. Sensitivity, Specificity and Accuracy were measured and the results were tabulated and are shown in Table VIII

The result shows that the performance measure of two classifiers outperforms better than three classifiers. And the performance is better when all the features are combined with two classifiers. Thus the result shows that Multiclass SVM and KNN classifier when combined with color, shape and texture feature produces the best performance result. It is then followed by SVM and KNN Classifier combined with all features. Moreover, it is also evident that the three classifier combination with all the features does not produce a good result.

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TABLE VIII: COMPARISON RESULT OF THE MULTIPLE CLASSIFIER-MULTIPLE FEATURE MODEL

COMPARISION RESULTS			
Classifier Technique	**SPECIFICITY**	**SENSITIVITY**	**ACCURACY**
12CS	78.9	87.13	83.9
12ST	80.1	88.71	84.59
12CT	85.9	92.18	87.47
12CST	87.8	95.65	90.12
23CS	82.39	95.8	93.31
23ST	86.24	96.2	94.39
23CT	88.3	97.28	96.57
23CST	**89.56**	**99.45**	**98.75**
13CS	77.16	93.1	89.2
13ST	79.38	94.87	90.48
13CT	82.78	96.33	91.18
13CST	85.15	98.3	93.7
123CST	73.4	90.4	88.27

T-Texture feature, C-Color Feature, S-Shape Feature
1-SVM Classifier, 2-Multiclass SVM Classifier, 3-KNN Classifier

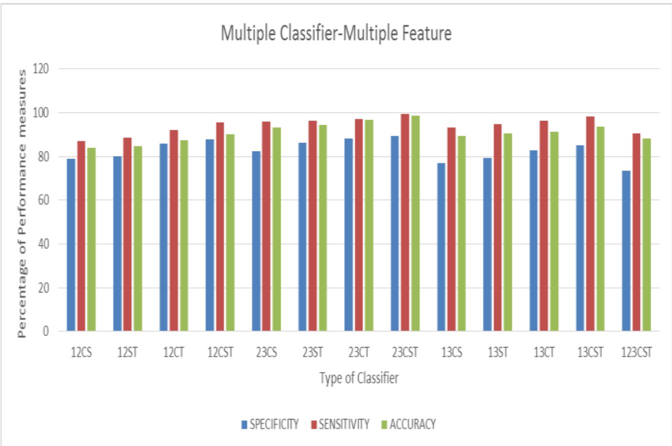


Fig 6: Performance Analysis of Multiple Classifier-Multiple Feature Model

VIII. GRAPHICAL USER INTERFACES

A. Nail Segmentation

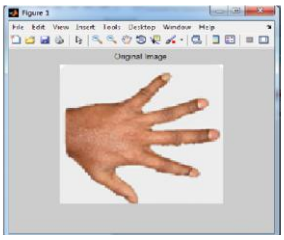
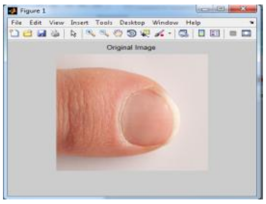


Fig 7: Original Palm Image



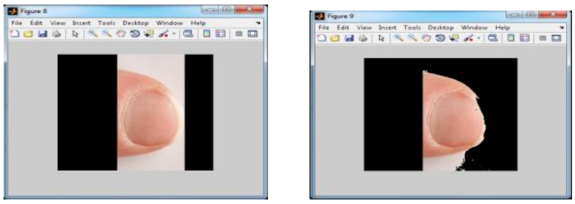


Fig 8: Nail Segmentation

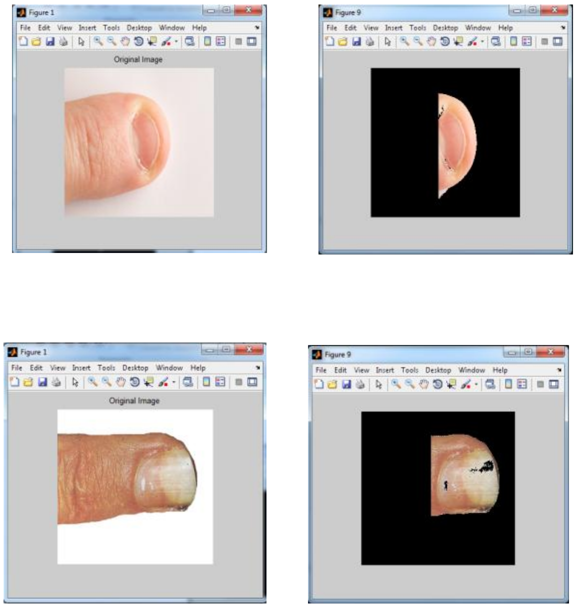
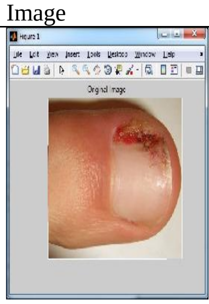
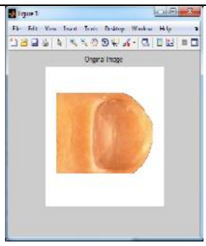
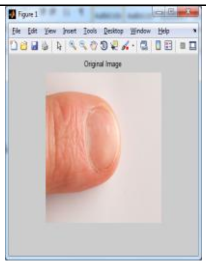
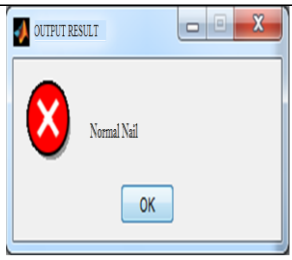


Fig 9 : Other Dataset Images

B. Disease Prediction

TABLE IX: OUTPUT RESULT

Si. No	Original Input Image	Disease Prediction Output
1		

2		
3		

IX. CONCLUSION AND FUTURE WORK

The ability to detect various diseases in their early stages is a very useful work for the society. This paper is based on Digital Image Processing, Ensemble of three classifier models namely SVM, Multiclass SVM and KNN with the three main features - Nail color, shape and texture for forming a feature vector. The nail analysis and prediction of various diseases is done by using the Hold out and Majority voting methods. The proposed system gives more accurate results than human vision, because it overcomes the limitations of human eye like subjectivity and resolution power. The detection system is a helping hand to the doctors so that they can give correct treatment to patients.

In this paper we have used an ensemble classifier model and compared three classifier techniques along with features for predicting various diseases through nail analysis. Here we have used 13 features and SVM, Multiclass SVM and KNN as the base classifiers. We have ensemble 46 classifier models and compared their results.

Here the study concludes that the ensemble classifier model of KNN and Multiclass SVM classifier with color, shape and texture features or these two classifiers with texture feature achieves the highest accuracy of 98.75 % followed by the ensemble model of SVM and KNN with features.

From the study we can also conclude that only models with two classifier combinations and all the three features produces the better results than three classifiers and on or two feature combinations. We can also conclude that texture feature give better results than other features. This study can be used for selecting the best classifier model for predicting various diseases through the analysis of human nail images. By varying the image processing techniques and Classifiers, the precision can be improved for this system. In future, we can combine other features of human body and predict various diseases based on the symptoms of patient and hence would be able to detect a lot of diseases with good precision and accuracy.

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