TEXTURE ANALYSIS AND DISEASE PREDICTION IN NAILS USING MACHINE LEARNING

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***Abstract*---Human nails are essential for diagnosing various illnesses at an early stage. In the field of medicine, a specific illness is discovered through analysis of a person's hand nail texture. We will conduct the survey on Machine learning classification model, which provides the accuracy of the results Texture Analysis in Nails using the Machine Learning Algorithm(CNN) proposed system enables us to decipher a model to investigate the nail texture and identify diseases early. Data Featured many data before processing the deep learning model. It takes short time to predict the disease. A person's image of their nails is the data provided to the system. The acquired image of the nails is processed and extracted using the feature extraction method. Here, the system is trained using CNN from images of a patient's particular disease-infected nails. Segmenting the nail portion allows for the extraction of nail shape and texture features, which are then compared to the training data. This analysis describes using machine learning algorithms to identify a person's disease earlier. We have given an algorithm with 87% accuracy.**

Keywords: *Disease identification, Feature analysis, CNN classifier, Nail Texture.*

1. INTRODUCTION

People can have conditions that may be underlying symptoms of serious diseases. Early detection of these diseases is important to increase the chance of overcoming them. However, people often fail to go to the hospital or seek professional medical help; they often simply search the Internet for the sources of their ailments. Without professional help, symptoms that were not recognized in the early stages of the disease can progress to further stages.

Tsuda et al, Finding that the distribution of pixels in the nail and skin regions are different, they proposed a nail detection method that exploits the variation in the distribution of pixels in the nail color. To perform the calibration procedure, the system used the color of the bail. The umbilical cord area is then extracted. This asymmetric extraction technique is based on the reflective properties of the nails and the nail and the position of the finger relative to the light source. This increases the accuracy of the nail segmentation.

Darshana A. A segmentation technique for automatic leaf disease detection developed by Darshana A Clustering techniques such as Mean-shift, K-means, and Fuzzy C-Means, and region-based image segmentation techniques such as region growth, region merging, region splitting, and region segmentation were used in this experiment. After segmentation, shape, and color features are extracted for each lesion point. Experimental results show that region growing is the most efficient technique to segment regions.

K. Dhana Shree, Everyone has unique nails. In the past, the mental state of the human body was reflected by the growth of the nail plate. Human nails can be diagnosed and disease predicted. Early prediction of disease can help prevent disease. In this proposed work, nail images were taken from microscopic images. The crescent and the nail plate are efficiently segmented using image preprocessing techniques. Directional gradient histograms and local binary models are used to record feature values. After preprocessing, various features are extracted from the spikes using various machine learning algorithms such as support vector machines, multiclass support vector machines, convolutional neural networks, and an optimization algorithm called optimization of ant colonies to improve classification efficiency.

Priya Maniyan. The NIPS-McS entry system is the back of the palm on a white background. Then, a region of interest (ROI), the nail region, is extracted from the palm image using the edge recognition method and the Canny segmentation process. Nail color, shape, and texture are then extracted and combined into a feature vector, which is then compared to an existing database of diseased and normal nails. The proposed system uses a multi-class SVM classification method to classify and predict diseases. It is very useful to work for society if one has the ability to recognize various diseases at an early stage. The proposed system, NIPS-McS, uses a classifier called multi-class SVM to analyze and predict nails after combining their color, shape, and texture characteristics to create a feature vector. The One-versus-Rest (1VR) approach of multi-class SVMs is used in the proposed system; it requires more training time than the one-versus-vs (1V1) approach, but generally works better. The model overcomes the limitations of human vision, such as subjectivity and resolution, to produce results that are more accurate than human vision.

SukdeepKaur et al analyze To obtain a clearly segmented image, various image segmentation techniques such as threshold segmentation, point transformation, watershed transformation and wavelet transformation can be used. Converts the compressed image to points using the logarithmic operator method by replacing each pixel value with the logarithm. Use watershed transformation to separate two merged objects. Sukdeep Kaur et al. Apply watershed transformation techniques to examine 2D image views from horizontal, vertical, and diagonal perspectives.

The Primary highlights of the proposed work are as followed:

- The overall objective of this study is to extract color features from nail images using digital image processing techniques to identify normal, anemic and disease caused by fungal infections.
- To evaluate transfer learning models such as VGG net, Alex net, Dense net, and Res net
- Comparison of the results of their transfer learning models for the classification of nails
- Secure the best Classification accuracy result

The paper is ordered as follows: Section 1 for introduction, Section 2 for the literature survey, Section 3 for Nail image identification & pre-processing phases, Section 4 for research methods, Section 5 for results and discussion, and finally, the Conclusion and future work in Section 6

2. LITERATURE SURVEY

The following is an overview of various disease detection studies using ear image analysis and related methods to detect leaf diseases. In this area of classification of human nail diseases, there are several ongoing studies using various methods. This section briefly presents various studies related to this work.

Pandit [1] provides a model that can be used to extract part of a provided image using color processing. They used the palm image as a starting point for their experiments, then separated the palm area from the rest of the image, examined the RGB components, retrieved the nail color image, and extracted the palm color of the extracted image. Nails were extracted from cropped images of the palm using RGB component analysis, and an algorithm was created to provide the average, pixel-by-pixel nail color for each digit. The experiments involved scanning people's backs and palms. 50 reference images of each color are used for comparison. They chose the reference shader after determining the arithmetic mean. They calculated the percentage of pixels in each nail that had a specific hue to identify the stage of the disease. The system is approximately 85% accurate. They proposed a technique to accurately recognize fingernails in images of hands (including palms) using distribution density and color continuity. Only between -90 to -40 degrees and 40 to 90 degrees can they reliably identify fingernails.

Bajpai et al [2] proposed a method to identify ROI by extracting features from human palms and fingernails, scanning human palms from both sides and an automatic prediction system for various health conditions. To predict the disease, they used symbols on the palm and the color of the nails. A backpropagation neural network approach was used to recognize symbols on human palms, which provided a disease prediction system with 90-95% efficiency. First, convert the RGB color image to a grayscale image for palm image processing, then use Frichen's edge detection algorithm on the palm image. The image is smoothed using morphological methods such as erosion and dilation, then the principal component analysis is used to generate vectors, and a similarity measure is used to generate the results.

Trupti [3] proposed a system for early disease detection by processing and extracting features from nail images. The training dataset was created from the nail images of the patients using the built-in tool. C (4.5) to build decision trees and develop color detection algorithms. According to their report, the algorithm matched the training dataset 65% of the time. Gandhat proposed extracting features from patient nail images and then applying a hair transformation matrix to produce feature vectors. After compressing the feature vectors using row means, compare them to the query feature vectors stored in the model dataset using similarity metrics such as MSE and absolute difference. By calculating the average RGB color of an ROI of a nail image.

Saranya [4] proposed an image segmentation method to identify nail abnormalities. To improve the efficiency of pre-processing, the median and average filters are combined for this effect, and then the image is converted to grayscale. To determine the shape of the nail, segmentation methods by watershed, threshold and k-means were used. Nail diseases are then determined using the extracted nail images.

Vipura et al.[5] Studies of nail color and texture indicate disease. However, looking at the color features, the model was only able to identify two or three diseases.. Limitations of the human eye, including subjectivity and resolution, can be overcome in all of the above models to predict disease quickly and economically.

Indrakumar S.S. [6] mainly struggled with detecting curves and straight lines. He first used the Sobel filter to remove noise from the image, then used the Canny algorithm to accurately detect the edge. In the image, the outline of the hand and the lines on the palm are extracted from the provided image using canny edge detection as the proposed solution to the palm problem. The process consists of five basic steps: image acquisition, selection of a region of interest, noise reduction using a Sobel filter, edge and line detection using a Canny algorithm and detection of eye problems when there are circles on the visor up. example.

The method proposed by Yani et al [7] also makes it possible to obtain color characteristics of nail images before examining specific diseases. Nijhawan et al created a deep learning-based method for nail disease recognition. They proposed a novel deep learning framework for image-based nail disease detection and classification. For feature extraction, the new algorithm integrates a convolutional neural network (CNN). The system was 84.58% accurate.

Vidhushavarshini S. [8] proposed a comparison for thyroid disease detection using J48 and Naïve Bayes classification techniques based on data analysis. The analysis helps in the accurate prediction of diseases by building the knowledge prediction model for the patients through analysis. They use J48 Paper Maker comparison and Naive Bayes classification techniques to achieve the best. For other classifiers, they use the WEKA tool. The result showed an accuracy of 81.94%. The Naive Bayes classifier shined with 51.77% accuracy. In the future, the J48 can be evaluated with another classification to achieve higher accuracy.

Sathiyabhama Balasubramaniam [9] proposed a hybrid optimization algorithm based on feature selection for thyroid disease classification. Thyroid hormone dysfunction has many negative effects on humans. In this paper, a feature selection design based on a hybrid optimization algorithm is adopted. Use type 2 coarse fuzzy support vector machine. They use the MKSVM approach. The HFBO-RT2FSVM model achieved an accuracy of 99.2a 8%, specificity, and sensitivity of 98% and 99.2%, respectively. They did not validate the model using a large data set; instead, they used 972 cases for the evaluation.

Takare [10]. The automated medical support system offered by Thakare uses technology based on Noval-Bi-cluster (bi-directional group) to identify human health problems. In this study, decision trees, neural networks, and support vector machines were used to collect and classify data from Medicinenet.com and Dermnet.com. Based on the analysis of nail color and texture, GLCM and bicolor algorithms are applied. After forming an input image using a neural network algorithm, a multilayer perceptron is used to classify the data. The analysis of the nail structure uses the Gray Scale Coincidence Matrix (GLCM). Using a neural network, the system was 88% accurate.

3. NAIL IMAGE IDENTIFICATION & PRE-PROCESSING PHASES

3.1 THRESHOLDING

Thresholding is a segmentation method that divides a grayscale image into two regions based on a threshold, from which a binary image is generated. Binary images are images in which pixels only have the values 0 and 1, requiring only a single bit to store pixel intensity. Thus, pixels in the output image with intensity values above the specified threshold are considered white or 1, while pixels with lower values are considered black or 0.

3.2 NOISE REMOVAL

Image noise is usually a component of electronic noise and is random fluctuations in image brightness or color information. This can be produced by the image sensor and circuitry of a scanner or digital camera. For noise reduction, the term "image noise" is often used. The word "noise" originally meant "unwanted signal", and perceived acoustic noise is produced by unwanted electrical fluctuations in the signal received by an AM radio. ("Stationary"). Image noise ranges from barely perceptible spots on digital photographs taken in good light to optical and radio astronomy images that are almost entirely noisy, but from which small amounts of information can be extracted using to sophisticated treatment. A photo with so much noise is unacceptable because it is difficult to identify the subject.

Here are some examples of image noise.

1. Exponential noise,
2. Rayleigh noise,
3. Shape noise,
4. Gaussian noise,
5. Salt and paper noise,
6. Erlang(gamma) noise.

3.2.1 EXPONENTIAL NOISE

When smoothing time series data using exponential window functions, the general rule is to smooth the data exponentially. A simple moving average weights past data equally, while an exponential function uses weights that decrease exponentially over time. Making decisions based on user-made assumptions, such as weather, is a simple process that's easy to learn and use. Exponential filtering is often used when analyzing time series data. One of the many window functions often used in signal processing to smooth data is exponential smoothing, which acts as a low-pass filter to remove high-frequency noise.

$$q(r) = \begin{cases} xe^{-\omega} & , \quad for\ r \geq 0 \\ 0 & , \quad for\ r < 0 \end{cases}$$

3.2.2 ERLAN (GAMMA) NOISE

Technically, random noise can be "represented" as a mathematical function. In fact, the model is just that. The probability is hidden under the "diffusion" of the noise. Therefore, the model is called a probability density function. (PDF). Once the noise has been measured, it is much easier to design filters to remove it. We will briefly review the different PDFs (Probability Density Functions) and in this article present six different noise models this article.

$$q(r) = \begin{cases} \frac{x^y z^{b-1}}{(y-1)!} e^{-xr} & , for\ r \geq x \\ 0 & , for\ r < x \end{cases}$$

3.2.3 RAYLEIGH NOISE

Gaussian distribution is another name. It has a probability density function (PDF) of a normal distribution. This noise includes sensor noise due to low light, high temperature, transmission, and transmission errors, such as B. Electronic circuit noise is added to the image during image capture. Spatial filtering, including mean filtering, median filtering, and Gaussian smoothing, can remove this noise by blurring the fine boundaries and details of an image. The following solution and illustration show Gaussian noise

$$\text{PDF:}q(r) = \frac{1}{\sqrt{2\pi\sigma}} e^{-(r-\mu)^2}$$

3.2.4 GAUSSIAN NOISE

Gaussian noise in digital images is mainly produced during the acquisition process. The amount of illumination and its own temperature make the sensor inherently noisy, and the electronic circuit connected to the sensor introduces its fair share of electronic circuit noise. An important part of an image sensor's "readout noise", or constant noise level in dark regions of the image, is amplifier noise. The probability density function q of a Gaussian random variable
is given by:

$$qG(r) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(r-\mu)^2}{2\sigma^2}}$$

3.2.5 SALT AND PAPER NOISE

Salt-and-pepper noise, spike noise, and fat-tail noise, or "impulse" noise, are other names for this type of noise. In an image with salt and pepper noise, dark pixels will appear in light areas and light pixels will appear in dark areas. Errors in the analog-to-digital converter or bit errors during transmission can cause this noise. Dark image subtraction, median filter, combined median and median filter, and interpolation around dark/light pixels can all eliminate it effectively. A similar but non-random display is produced by dead pixels in the LCD panel.

$$q(r) = \begin{cases} q_x & for\ r=x \\ q_y & for\ r = y \\ 0 & otherwise \end{cases}$$

3.2.6 SHAPE NOISE

Noise is a crucial component that is incorporated into it. During the processes of capture, encoding, transmission, and processing, noise is always present in digital pictures. Without the right filtering methods, it is very difficult to remove noise from digital pictures.

$$Q(r)\frac{1}{A(r)}$$

3.3 NORMALIZATION

Another step in the detection and preprocessing of nail images. An image processing method called normalization is used to improve an image's quality and clarity. In the case of nail images, normalization can help to improve the accuracy and effectiveness of subsequent analysis, such as nail disease detection. In the case of nail diseases, normalization refers to the restoration of the nail's natural appearance and function. It's essential to remember that based on the specific condition and severity of the disease, the normalization process for nail disease may vary. To create a therapy strategy that is specific to each patient's requirements, patients and their healthcare providers should collaborate closely.

4. RESEARCH METHODS

4.1 IMAGE PREPROCESSING AND DATASET

The work presents a useful nail dataset. We have collected datasets from NSD(Nail Segmentation dataset),TBND,(transient Biometric Nail Dataset), TBND(Nail Disease Detection Image), NDDI (Nail Disease Detection Image)and, NFD Nail Fungal Dataset. NSD has 204 nail images and consists of 306 images. NDDI, it has 300 images of bail the dataset and NFD consists of 1200 nail images.

Table.1 Data set

NO	Dataset	No.of Image data
1	NSD	204
2	TBND	306
3	NDDI	300
4	NFD	1200

4.2 DATA WORKFLOW

Features were extracted from the nail image files using 32 different transfer learning techniques. To identify people and gender, two different feature files are extracted from the images. Divide the data into training and test sets using a 10-fold cross-validation technique. With this approach, data is first divided into 10 separate categories, one for testing and nine for training. Then switch groups ten times after this process to use all the nail image data in the dataset for testing and training purposes. In order to achieve the highest classification success rate, 28 different classification algorithms were tried on the generated profile for person and gender. Transfer learning techniques, classification algorithms, and study success rates are included in the Results section.

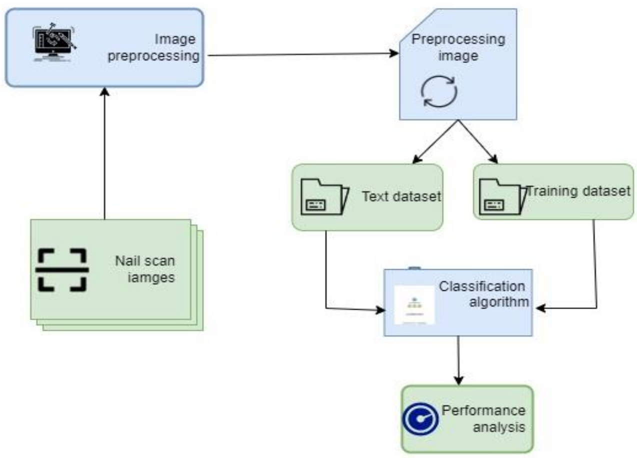

Fig.1.Transfer learning methods

4.3 RANDOM FOREST CLASSIFICATION METHOD

Many decision trees are constructed during training to create random forests or random decision forests, an ensemble learning technique for classification, regression, and other tasks. The class chosen by the largest number of trees is the random forest output in the classification task. The mean or mean prediction for each tree is given in the regression task. Random decision forests correct the tendency of decision trees to overfit their training set. Although they often beat decision trees, random forests are not as accurate as gradient-enhanced trees. The two steps of the random forest operation are to build a random forest by combining N decision trees and to make a prediction for each tree built in the first step.

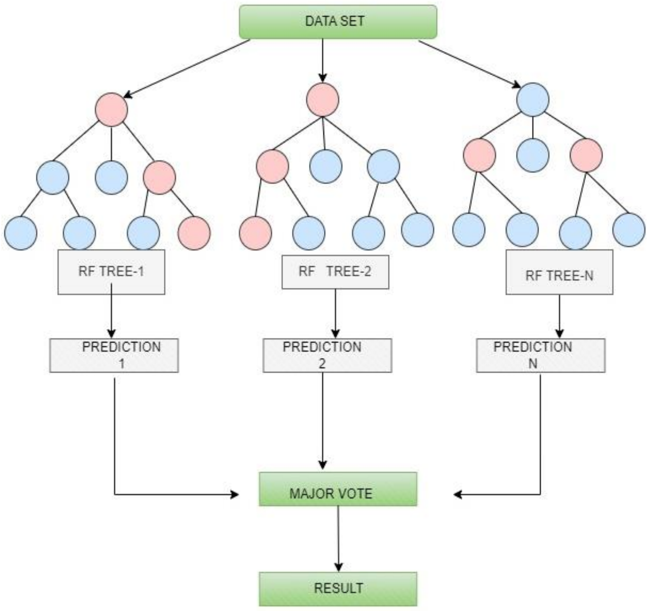

Fig.2 Random Forest Classifier

4.4 TRANSFER LEARNING ALGORITHM

4.4.1 RESNET

In 2015, researchers from Microsoft Research introduced a new architecture called Residual Network under the proposal of Res Net. Residual network: This architecture introduces the idea of residual blocks to solve the gradient vanishing/exploding problem. We use an approach called "jumping connections" in this network.

4.4.2 ALEXNET

Each subsequent winning design builds on the first CNN-based architecture (AlexNet), which won the ImageNet 2012 competition by reducing error rates. This works for fewer layers, but as we add more layers, a deep learning problem called "disappearing/exploding gradients" becomes common. Therefore, as we add more layers, the error rate in training and testing increases. We can see that the 20-layer CNN design has a lower error rate in testing than the 56-layer design. After further investigation, the authors conclude that the error rate is caused by the disappearance of the exposure gradients.

4.4.3 VGGNet

The VGGNet recommended by Visual Geometry Group (VGG) members Simonyan and Zisserman has over 14 million data points and 1000 classes and had a major impact on the 2014 ILSVRC Championship. So it turns out that increasing the depth with smaller filters gives better results than widening the grating. There are two different models in the VGGNet architecture, each with 16 or 19 layers. The model has 13 convolutional layers and 3 fully connected layers.

4.4.4 DENSE NET

Using dense blocks directly connected to each layer, DenseNet is a specific type of convolutional network that uses dense connections between layers. (with corresponding feature map size). Each layer receives additional input from all previous layers to preserve input properties and passes its own feature map to all subsequent layers.

4.5 DATA SEPARATION FOR TRAINING AND TESTING DATA

Before classification, the resulting dataset must be divided into training and test sets. Building accurate predictive models on decomposed training datasets and evaluating model accuracy on new data are the main goals of machine learning algorithms. The model test data set provides data to confirm the correctness of the model. Using random percentages (such as 80% for training and 20% for testing) is the easiest way to divide your training and testing data sets. When determining the training and test data for a model, there will be an error in dividing the data into percentages, depending on the distribution of the data. The cross-validation technique is used to divide all data into training and test datasets to avoid this situation. The data was first divided into 4 independent groups, one of which was used for testing, and the other nine were used for training. This process is carried out 4 times. The final success rate was then determined by averaging the classification successes for each procedure. (Aydemir and Al-Azzawi, 2021). The figure below illustrates this situation.

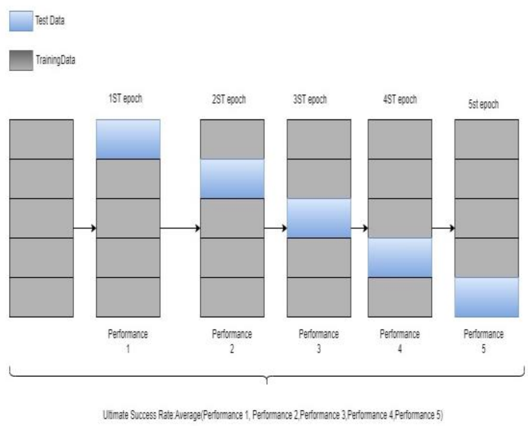

Fig.3 Tenfold cross-validation method

4.6 PERFORMANCE METRICS

Performance evaluation of handwriting detection systems using confusion matrices. The columns of the confusion matrix are a 2x2 matrix containing the actual samples belonging to each class, while the rows reflect the estimated sample data belonging to each class. Row and column values can also be compared when constructing a confusion matrix. (Power, 2011). Accuracy, memory, precision, and F1 score values were calculated using the confusion matrix in Table 3 below.

Table 1 Performance Metrics

	ACTUAL CLASS	
	True	False
POS (+ve)	True (+ve) TP	False (-ve)FP
NEG (-ve)	False (-ve) FN	True (+ve) TN

ACCURACY

Accuracy is simply a measure of how often the classifier makes correct predictions. It is the ratio between the number of correct predictions and the total number of predictions.

$$accuracu = \frac{TP+TN}{TP+FP+TN+FN}$$

RECALL

A recall is a good evaluation metric when we want to capture as many positives as possible.

$$\text{TPR}=\frac{TP}{TP+FN}$$

PRECISION

Precision is the ratio of the number of accurately predicted correct nail image samples to the total number of nail image samples correct as determined by the verification system. Precision is given by the following equation:

$$TPV = \frac{TP}{TP+FP}$$

F1-SCORE

This represents the harmonic mean of the Precision and Recall numbers. The following algorithm produces the F1 score:

$$F1 = \frac{2 * TPV * TPR}{TPV + TPR}$$

5. RESULT AND DISCUSSION

Nail image data from 25 people was used in the study. The table below uses a total of 15 distinct transfer learning techniques to extract image features in the data. Each signature file is tested using the random forest technique and the one with the highest success rate is selected.

Table 2 Transfer Learning Method

NO	Transfer Learning Method	Accuracy rate
1	EfficientNetB7	0.871929825
2	MobileNet	0.784210526
3	ResNet152	0.784210526
4	EfficientNetV2L	0.775438596
5	EfficientNetV2S	0.773684211
6	VGG19	0.773684211
7	EfficientNetB3	0.771929825
8	MobileNetV2	0.752631579
9	NASNetLarge	0.735087719
10	DenseNet121	0.726315789
11	EfficientNetV2M	0.726315789
12	InceptionV3	0.71754386
13	Xception	0.673684211
14	AlexNet	0.670175439
15	InceptionResNetV2	0.524561404

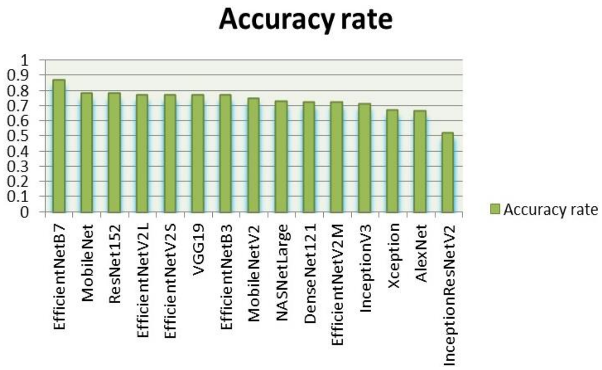

Fig.4.Result classification

The EfficientNetB7 transfer learning algorithm has the highest success rate as shown in Table 2, which is 87.19%. The extracted personal data used in the EfficientNetB7 transfer learning method was split into 20% test data and 80% training data before being tested with 28 different classification algorithms. The table below shows user conclusions about EfficientNetB7 features achieved using various classification algorithms.

Table 3 Classification algorithm

NO	Classification Method	Accuracy	F1	Recall	Precision
1	Linear model.Ridge Classifier	0.8737	0.8734	0.8735	0.8754
2	Linear model. Logistic Regression	0.8676	0.8679	0.8669	0.8682
3	Neighbors. Kneighbors Classifier	0.8661	0.8650	0.8650	0.8667
4	Svm .Nu SVC	0.8663	0.8654	0.8646	0.8693
5	Ensemble .Random ForestClassifier	0.8645	0.8636	0.8635	0.8684
6	Discriminant analysis. LinearDiscriminantAnalysis	0.8634	0.8627	0.8623	0.8639

7	Linear model. Perceptron	0.8562	0.85 46	0.85 37	0.8750
8	Ensemble .Voting Classifier	0.8385	0.83 67	0.83 62	0.8470

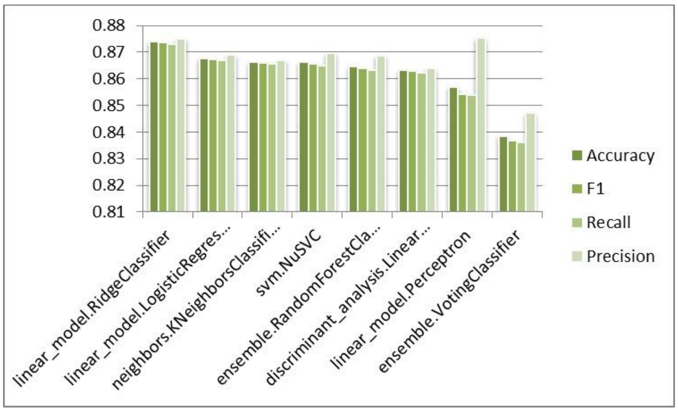

fig .5. Classification Algorithm

Table 3 shows the precise classification rates obtained along with the details of the algorithm. The linear model produced the most accurate classification, with the RidgeClassifier method achieving an accuracy of 87.38%. The table of results for Hit Rate, Accuracy, Sensitivity, and F-Score shows that Personal Verification produces very good results. These results demonstrate that people variables can be successfully identified and verified from Nail Pictures.

6. CONCLUSION :

Texture analysis and disease prediction in nails using machine learning is a promising approach for early diagnosis and treatment of nail diseases. In this technique, texture features are extracted from images of nails, which are then used to train machine-learning models for nail disease prediction. Using machine learning algorithms, this approach can accurately detect nail diseases and distinguish them from healthy nails. This can lead to earlier detection and treatment of nail diseases, which can improve patients' overall health and quality of life. analyzing all papers, we take the number of datasets of four. We have given an algorithm with 87% accuracy. In our upcoming effort, we intend to investigate additional classification enhancement.

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