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Authors: Serkan DÜZAYAK, Muhammed Kürşad UÇAR

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A Novel Machine Learning-based Diagnostic Algorithm for Detection of Onychomycosis through Nail Appearance

Serkan DÜZAYAK [1], Muhammed Kürşad UÇAR [*2]

Abstract

Onychomycosis is the most common nail fungus disease in clinical practice worldwide, caused by the localization of various fungal agents, including dermatophytes, on the nail. The tests traditionally used for diagnosing onychomycosis are native examination, histopathological examination with periodic acid Schiff (PAS) staining, and nail culture. There is no gold standard method for diagnosing the disease, and the diagnosis process is time-consuming, costly, and quite laborious. Today, new technologies are needed to detect onychomycosis via AI-based ML to reduce the clinician and laboratory-induced error rate and increase diagnostic sensitivity and reliability. The present study aimed to design a decision support system to help the specialist doctor detect toenail fungus with artificial intelligence-based image processing techniques. The toenail images were taken by any camera initially from the individuals referred to the clinic. The image is divided into 12 RGB channels. Three hundred features were removed from each channel as 25 in the time domain. The best features were selected through feature selection algorithms in the next step to increase the performance and reduce the number of features, and models were created by algorithm classification. The average performance values of all proposed models, accuracy, sensitivity, and specificity, are 89.65, 0.9, and 0.89, respectively. The performance values of the most successful model-created accuracy, sensitivity, and specificity are 97.25, 0.96, and 0.98, respectively. Although the proposed method, according to the findings obtained in the study, has many advantages compared to the literature, it can be used as a decision support system for clinician diagnosis.

Keywords: Onychomycosis, nail fungus, image processing, artificial intelligence, machine learning

1. INTRODUCTION

Onychomycosis is the most common nail fungus disease in clinical practice in the world caused by the localization of various fungal agents including dermatophytes on the nail [1], [2]. The risk of onychomycosis increased by aging. Furthermore, tinea pedis history, trauma, obesity, diabetes mellitus are other risk factors [3]. The condition constitutes a public health problem because it is transmitted from person to person and through direct contact with contaminated surfaces. Furthermore, the quality of life of

* Corresponding author: mucar@sakarya.edu.tr (M.K. UÇAR)
[1] Adıyaman University, Faculty of Medicine, Department of Dermatology and Veneral Diseases, Adıyaman, Türkiye
[2] Sakarya University, Faculty of Engineering, Electrical and Electronics Engineering, Serdivan, Sakarya, Türkiye
E-mail: sduzayak@adiyaman.edu.tr
ORCID: https://orcid.org/ 0000-0002-4853-9860, https://orcid.org/ 0000-0002-0636-8645

patients is impaired due to aesthetic problems caused by deformities in the nails, localized pain in dystrophic nails that may affect the daily life [4].

The tests which are traditionally used for the diagnosis of onychomycosis are native examination (microscopic KOH test), histopathological examination with periodic acid schiff (PAS) staining, and nail culture. None of these tests are considered a stand-alone standard test. The combined use of the tests may increase the sensitivity and specificity. However, there is not any consensus on the most appropriate test combination. The most important disadvantage is that the nail culture which is another diagnostic method may provide a result after 3 weeks at least, and the culture procedure bears the risk of contamination. Another diagnostic test is histopathological examination with PAS staining; however, this test poses a disadvantage because it cannot be applied to all patients and is expensive [5]. The KOH analysis is more practical and cheaper than other methods. However, limitations of this test include variable sensitivity between 44% and 100%, the possibility of being affected by experience of the clinician, and average testing period between 30 and 60 minutes.

Since the visual diagnosis is at the forefront, dermatology is increasingly involved in artificial intelligence (AI) studies. Machine learning (ML) is a component of AI which recognizes models synthesized from data and automatically teaches the tasks to the machines [6]. Although AI and ML have been developed in dermatology mostly for the diagnosis of melanoma and non-melanoma cutaneous tumors, they are also used for evaluation of psoriasis, atopic dermatitis, cutaneous ulcers and detection of onychomycosis [7-11]. Today, new technologies are needed for the detection of onychomycosis via AI-based ML in order to reduce the clinician and laboratory-induced error rate and increase diagnostic sensitivity and reliability.

The artificial intelligence algorithms have been used frequently in the field of dermatology in the recent years [12-14]. These applications include skin cancer detection [13, 15]. It is possible to create artificial intelligence-based decision support systems with every image taken from the skin, such as psoriasis, onychomycosis and acne [12]. Artificial intelligence methods have started to be preferred frequently in the dermatological oncology [12]. Deep learning artificial intelligence algorithms are preferred since applications with image processing frequently have higher performance value [16-19]. The most significant disadvantage of deep learning is requirement of much when compared to classical machine learning algorithms [18].

Onychomycosis is one of the diseases that is frequently studied in dermatology. The disease may be diagnosed with microscopic images as well as artificial intelligence-based diagnosis with skin images [14]. The model offered in this study works with microscopic images with a achievement rate of 95.9% based on artificial intelligence. It was stated in the aforesaid study that the clinician may diagnose with an accuracy rate of 72.8%. Microscopic images are needed for diagnosis in the relevant study. The present study offers a method that diagnosis may be established with clinical images of nails without the need for microscopic images. The diagnosis period thereby may become shorter.

The accuracy rate of a proposed model based on artificial intelligence for the diagnosis of onychomycosis has been reported to be 84.58% [20]. Disease diagnosis in dermatology is based on tissue and color analysis [21]. The color and tissue changes appear in the course of onychomycosis. In this case, diagnosis can be made by using color analysis with the help of image processing techniques [22, 23]. The mainstay of artificial intelligence and image processing studies is color analysis and the perception of this color difference by the artificial intelligence.

In two different studies, the accuracy rates of the deep learning-based diagnostic system were reported as 65% with the nail images obtained from Kaggle [24, 25]. The accuracy rates ıf both studies are quite lower. A previous study conducted by Han et al. in 2018 developed a diagnostic model through a data set of approximately 50 thousand nail images with deep learning-based methods such as CNN, R-CNN, ResNet-152, and VGG-19 [8]. The sensitivity of model performance values ranged between 87.2 and 96.7, the specificity was between 69.3 and 96.7, and AUC value ranged between 0.82 and 0.98. These high-performance values are an indication that artificial intelligence may be used in dermatology. Kim et al. offered CNN deep learning model in a different study [26]. The sensitivity and specificity values of the model performance were 70.2 and 72.7, respectively. The sensitivity and specificity of labeling done by 5 dermatologists were 73 and 49.7 in the aforesaid study. It is noteworthy that the artificial intelligence model has a higher achievement rate than dermatologists.

Unlike the literature, the aim of the present study was to detect Onychomycosis with a high achievement rate with the help of classical machine learning algorithms instead of deep learning methods. This study aims to design a decision support system that would help the specialist doctor for the detection of toenail fungus with artificial intelligence-based image processing techniques. The procedures are carried out as follows in a referring individual in the study. In the first step, toenail images are taken from the individual with the help of any camera. The noise is removed from the captured images with the help of digital filters. The clarified images are split into 12 RGB channels for more information extraction. Twenty-five (25) features are extracted in the time domain from each channel information. A total of 300 extracted features become parameters representing images. The best features were selected through feature selection algorithms in the next step in order to increase the performance and reduce the number of features. After this stage, classification models are created through data sets created with selected features. The created models are ready for use in the clinic.

2. MATERIAL AND METHOD

The present research was carried out within the frame of the steps shown in Figure 1. The aim of the study is to detect nail fungus based on artificial intelligence with nail fungus images. Within this context, the data were collected from individuals to create an artificial intelligence model. The images were then cleared through digital filters and separated into RGB channels. Different images were obtained during the filtering. Feature extraction was performed from the obtained image channel information. Relevant features are selected with the help of feature selection algorithm. The artificial intelligence trainings were carried out through different machine learning algorithms at the last stage. The detailed additional information for the process steps is given in the sub-titles.

2.1. Data Collection

This research includes sick and healthy nail images collected from 76 individuals who have referred to dermatology and venereal diseases polyclinic of Sakarya Karasu Public hospital between 02/01/2020 and 02/01/2021 (Table 1.).

Table 1 The distribution of gender-based age individual count

	Male	Female	Total
n	39	37	76
Mean	37.18	33.30	35.29
Std	13.85	13.34	13.65
Min	18	18	18
Max	67	60	67

n: number of individuals

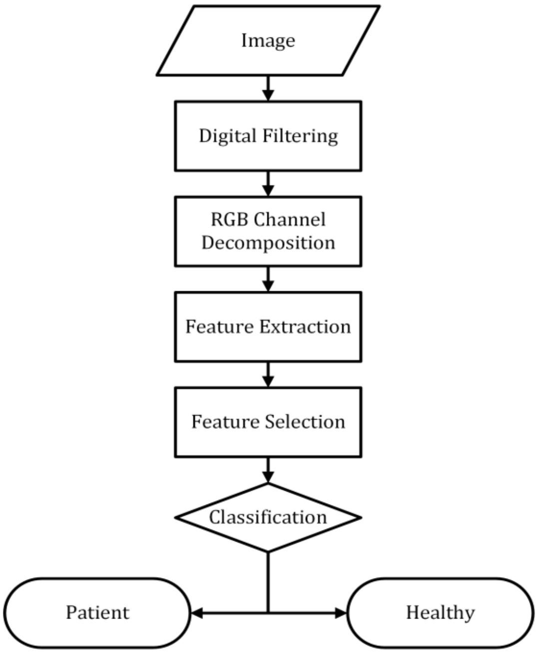

Figure 1 Study implementation process

Nail images collected from a total of 76 individuals including 39 males and 37 females were classified as fungal disease or healthy by the specialist within the framework of examinations (Table 2.). In other words, more than one image was taken from an individual.

Table 2 Distribution of the images as sick, healthy, and gender-based

	Male	Female	Total
Patient	155	87	242
Healthy	139	307	446
Total	294	394	688

2.2. Image Preprocessing

Totally 688 nail images collected from individuals were preprocessed (Figure 2.). As a first step, the nail image on each finger was trimmed rawly. Manual segmentation was performed on the trimmed image. A mask was created for each image. Image smoothing was performed by applying an average filter to the segmented image. The Hue Saturation Value (HSV) image of both filtered and unfiltered image was obtained. As a result of this process, four images including the original, the original mean filtered, the original HSV and the filtered HSV image appeared. The RGB channels of each image are separated and the image is rendered processable. After this stage, the feature will be extracted from each RGB channel.

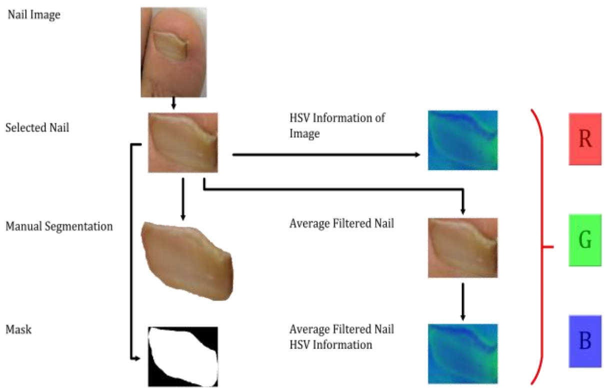

Figure 2 Detailed visual representation of the signal processing process

The steps and step outputs related to the process of filtering the original image and obtaining the HSV information are shown in detail in Figure 3.

2.3. Feature Extraction

After the processing steps of the images, four images (Orginal Image, Average Filtered İmage, Original Image HSV Information And Average Filtered Nail HSV Information, Figure 3.) and their 12 RBG channel information were obtained for each nail image. A total of 300 features were extracted from each channel, including 25 statistical features in the time domain (Table 3.).

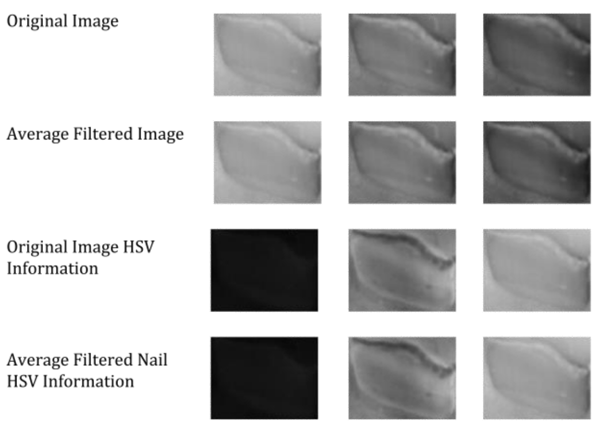

Figure 3 The change of the images after filtering.

The features were released in the MATLAB environment and the MATLAB library was used for some features. Özellik çıkarma oldukça önemli bir süreçtir. Feature extraction is a very important process. The extracted features should describe the signal well. It is known that statistical-based feature extraction processes, which are thought to describe data sets well in previous studies, affect performance quite well. For this reason, the study was carried out using the features used in the literature before [27-31].

2.4. Feature Selection

Three hundred (300) features were extracted from four images and 12 RGB channels for a nail image until this stage. The aim of the feature selection step is to improve the performance of machine learning by weeding out irrelevant features.

A previous study in which the Eta feature selection algorithm was compared with other algorithms states that it could be more efficient than existing algorithms in terms of performance [27].

Eta feature selection algorithm is used to select features to increase model performance.

The feature selection algorithm based on the eta correlation coefficient performs the selection process between the unordered qualitative (Sick/ Healthy) variables and the continuous numerical variables (the average pixel value of the image) according to the level of the correlation coefficient.

Table 3 Mathematical equations for the features [27]

No.	Feature	Equation
1	Kurtosis	$x_{kur}=\sum_{i=1}^{n}(x(i)-\bar{x})^4/(n-1)S^4$
2	Skewness	$x_{ske}=\sum_{i=1}^{n}(x_i-\bar{x})^3/(n-1)S^3$
3	* IQR	$IQR=iqr(x)$
4	DK	$DK=(S/\bar{x})100$
5	Geometric Mean	$G=\sqrt[n]{x_1+\cdots+x_n}$
6	Harmonic Mean	$H=n/\left(\frac{1}{x_1}+\cdots+\frac{1}{x_n}\right)$
7	Activity - Hjort Parameters	$A=S^2$
8	Mobility - Hjort Parameters	$M=S_1^2/S^2$
9	Complexity - Hjort Parameters	$C=\sqrt{(S_2^2/S_1^2)^2-(S_1^2/S^2)^2}$
10	* Maximum	$x_{max}=max(x_i)$
11	Median	$\tilde{x}=\begin{cases}x_{\frac{n+1}{2}} & : x \text{ odd}\\ \frac{1}{2}(x_{\frac{n}{2}}+x_{\frac{n}{2}+1}) & : x \text{ even}\end{cases}$
12	* Mean Absolute Deviation	$MAD=mad(x)$
13	* Minimum	$x_{min}=min(x_i)$
14	* Central Moments	$CM=moment(x,10)$
15	Mean	$\bar{x}=\frac{1}{n}\sum_{i=1}^{n}=\frac{1}{n}(x_1+\cdots+x_n)$
16	Average Curve Length	$CL=\frac{1}{n}\sum_{i=2}^{n}\lvert x_i-x_{i-1}\rvert$
17	Average Energy	$E=\frac{1}{n}\sum_{i=1}^{n}x_i^2$
18	Root Mean Squared	$X_{rms}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\lvert x_i\rvert^2}$
19	Standard Error	$S_{\bar{x}}=S/\sqrt{n}$
20	Standard Deviation	$S=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})}$
21	Shape Factor	$SF=X_{rms}/\left(\frac{1}{n}\sum_{i=1}^{n}\sqrt{\lvert x_i\rvert}\right)$
22	* Singular Value Decomposition	$SVD=svd(x)$
23	* 25% Trimmed Mean	$T25=trimmean(x,25)$
24	* 50% Trimmed Mean	$T50=trimmean(x,50)$
25	Average Teager Energy	$TE=\frac{1}{n}\sum_{i=3}^{n}(x_{i-1}^2-x_ix_{i-2})$

* The feature was computed using MATLAB
IQR Interquartile Range, DK Coefficient of Variation

The algorithm calculates a correlation coefficient between each feature of the image and the image tag (r) [32]. The r coefficient is called the inter-correlation coefficient Eta. Calculated correlation coefficients are rated between 0 and 1, with 1 indicating the best correlation. The features are arranged in order of relevance by arranging the r values from the largest to the smallest. After this stage, models are created by selecting the best X% features in order to determine how many features would affect the performance. The X indicates the percentage quantity that is wanted to be selected. In this study, 20 different values were determined by increasing the X value between 5 and 100 with 5 step intervals. The models created with each value are called levels. As the feature selection level is increased, in other words, as the X value is increased, new datasets are created. Twenty feature groups were created at the end of this process.

2.5. Machine Learning

In this research, three basic machine learning methods were preferred due to their higher performance. The first of these is artificial neural networks (ANN) which are the basis of deep learning [33, 34]. ANN is an algorithm that has higher performance as classical machine learning algorithms and fast deep learning. The performance could be made quite higher depending on the type of problem. The deep learning models are the right choice, especially for problems where direct processing of images is required; however, ANN can remain at the basic level. However, as the complexity of the problem decreases, preferring ANN models may be the right choice. The biggest challenge during ANN trainings is performing the parameter optimization depending on the data set. Therefore, many trials should be done by changing the ANN parameters for different datasets during the training. This number of trials may be up to millions. Some parameters may be kept constant in order to reduce the number of trials. For example, trainlm is one of the most optimized structures among ANN training algorithms. Therefore, keeping such parameters constant will reduce the number of trial variances.

Another algorithm is the Support Vector Machine (SVM) used in classical machine learning [35, 36]. SVM is one of the classical machine learning algorithms with higher adaptability to datasets, higher performance and shorter training time in general. The aim of the algorithm is to create an n-dimensional plane that will divide the dataset into two classes. The dataset is sized depending on the number of features. The algorithm has two basic working structures including linear and non-linear. Depending on the suitability of the data set, this structure may be preferred by the user.

The last method is Ensemble Decision Trees (EDT) containing a hybrid structure [37, 39]. Ensemble structures are generally hybrid structures created by combining more than one algorithm. These hybrid structures take the average of decisions given by all algorithms in the structure and reflects to the output. The output may be found by the average or weighted grading. This means that the effect of each machine learning on the output is determined by proportioning it between 0 and 1. The algorithm with the highest performance would be more effective. In this type of structures, it is often preferred because the error rate decreases, and single classifiers come together to create models with higher performance.

CNN is a new artificial intelligence algorithm that is frequently used today. However, high performance computers or servers are required for its use. Since high-performance computers are costly, classical machine learning algorithms are preferred in this study. In order for the success rate to be at the same level with deep learning methods, innovations have been made in the signal processing process [8, 9, 26].

2.6. Performance Assessment Criteria

In this study, six performance evaluation criteria which are frequently used in the literature were preferred. These include accuracy, sensitivity, specificity, F-Measure, Kappa coefficient, and AUC value. The equations of the parameters may be accessed via relevant reference [40]. The models were divided into two as training by 80%, and test by 20% (Table 4.).

Table 4 The data distribution for training and test process

The dataset	Training (80%)	Test (20%)	Total
Patient:	193	49	242
Healthy	244	60	304

3. RESULTS

The aim of the study is to detect nail fungus with artificial intelligence-based nail images. The data collected in the polyclinic were obtained from 688 nail images of 76 individuals with 242 sick and 446 healthy nail images. A total of 12 images were obtained by preprocessing each image (Figure 2.). After preprocessing, 25 features were extracted from each image and 300 features were extracted from 12 images in total (Table 3.). Eta feature selection algorithm is used to improve machine learning models.

The features are selected with a certain amount through the feature selection algorithm, and models at different levels are created (Table 5.). The best result in the table is marked in red. The level 1 model was created by selecting the best 5% features. The models were created with three machine learning at this level. A total of 15 features were selected with 5% features. Thirty features were selected with the best 10% features for the level. Tree models were created with three machine learning at this level. The achievement rate reaches its maximum when the amount of features increases and reaches by 90%. The achievement rate was 79.82 at 5%, and 97.25% at 90%. Balance and higher levels are expected in other parameters as well as accuracy rate. The sensitivity and specificity values of the model created with 5% feature are 0.84 and 0.83. Such values are 0.96 and 0.97 with a feature by 90%. The closeness of these ratios indicates that the model is stable and balanced. In the graphical representation of the performances, it has been determined that the performance increases when the number of features increases (Figure 4.) . Different performance values are compared on the spider chart for the best performance Level 10 and 18 (Figure 5.). Different performance values are compared on the spider chart for the best performance Level 10 and 18. It was determined that the EDT model for level 18 and the SVMS model for level 10 were the most efficient.

The model performance values proposed in this study were compared with the results of the studies in the literature (Table 6, 7.). The reason for the proposed model being better than others stated in the literature may be the steps in the image processing processes. The difference here is the methods chosen in the feature extraction, feature selection, and classification stages.

Table 5 Model performances

Info	Performance Evaluation Criteria					
L=1, NF=15, FP=5						
Model	**Acc**	**Sen**	**Spe**	**F-O**	**Kappa**	**AUC**
CNet	83.49	0.84	0.83	0.84	0.67	0.84
EDT	80.73	0.84	0.78	0.81	0.61	0.81
SVMs	79.82	0.88	0.73	0.80	0.60	0.81
L=2, NF=30, FP=10						
Model	**Acc**	**Sen**	**Spe**	**F-O**	**Kappa**	**AUC**
CNet	83.49	0.82	0.85	0.83	0.67	0.83
EDT	84.40	0.86	0.83	0.85	0.69	0.85
SVMs	86.24	0.90	0.83	0.86	0.72	0.87
L=3, NF=45, FP=15						
Model	**Acc**	**Sen**	**Spe**	**F-O**	**Kappa**	**AUC**
CNet	87.16	0.86	0.88	0.87	0.74	0.87
EDT	87.16	0.88	0.87	0.87	0.74	0.87
SVMs	79.82	0.80	0.80	0.80	0.59	0.80
L=4, NF=60, FP=20						
Model	**Acc**	**Sen**	**Spe**	**F-O**	**Kappa**	**AUC**
CNet	83.49	0.84	0.83	0.84	0.67	0.84
EDT	88.99	0.90	0.88	0.89	0.78	0.89
SVMs	82.57	0.82	0.83	0.82	0.65	0.82
L=5, NF=75, FP=25						
Model	**Acc**	**Sen**	**Spe**	**F-O**	**Kappa**	**AUC**
CNet	88.07	0.88	0.88	0.88	0.76	0.88
EDT	89.91	0.90	0.90	0.90	0.80	0.90
SVMs	88.99	0.90	0.88	0.89	0.78	0.89
L=6, NF=90, FP=30						
Model	**Acc**	**Sen**	**Spe**	**F-O**	**Kappa**	**AUC**
CNet	92.66	0.90	0.95	0.92	0.85	0.92
EDT	93.58	0.94	0.93	0.94	0.87	0.94
SVMs	90.83	0.90	0.92	0.91	0.81	0.91
L=7, NF=105, FP=35						
Model	**Acc**	**Sen**	**Spe**	**F-O**	**Kappa**	**AUC**
CNet	89.91	0.86	0.93	0.89	0.79	0.90
EDT	92.66	0.90	0.95	0.92	0.85	0.92
SVMs	89.91	0.92	0.88	0.90	0.80	0.90
L=8, NF=120, FP=40						
Model	**Acc**	**Sen**	**Spe**	**F-O**	**Kappa**	**AUC**
CNet	92.66	0.90	0.95	0.92	0.85	0.92
EDT	91.74	0.90	0.93	0.92	0.83	0.92
SVMs	88.99	0.86	0.92	0.89	0.78	0.89
L=9, NF=135, FP=45						
Model	**Acc**	**Sen**	**Spe**	**F-O**	**Kappa**	**AUC**
CNet	90.83	0.90	0.92	0.91	0.81	0.91
EDT	89.91	0.92	0.88	0.90	0.80	0.90
SVMs	90.83	0.90	0.92	0.91	0.81	0.91
L=10, NF=150, FP=5						
Model	**Acc**	**Sen**	**Spe**	**F-O**	**Kappa**	**AUC**
CNet	**92.66**	**0.92**	**0.93**	**0.93**	**0.85**	**0.93**
EDT	**93.58**	**0.96**	**0.92**	**0.94**	**0.87**	**0.94**
SVMs	**93.58**	**0.96**	**0.92**	**0.94**	**0.87**	**0.94**

L: Level, NF: Number of Feature, FP: Percentage of Feature

Table 5 Model performances (continuance)

Info	Performance Evaluation Criteria					
L=11, NF=165, FP=50						
Model	**Acc**	**Sen**	**Spe**	**F-O**	**Kappa**	**AUC**
CNet	88.07	0.88	0.88	0.88	0.76	0.88
EDT	96.33	0.94	0.98	0.96	0.93	0.96
SVMs	88.07	0.90	0.87	0.88	0.76	0.88
L=12, NF=180, FP=60						
Model	**Acc**	**Sen**	**Spe**	**F-O**	**Kappa**	**AUC**
CNet	91.74	0.92	0.92	0.92	0.83	0.92
EDT	96.33	0.96	0.97	0.96	0.93	0.96
SVMs	88.99	0.94	0.85	0.89	0.78	0.89
L=13, NF=195, FP=65						
Model	**Acc**	**Sen**	**Spe**	**F-O**	**Kappa**	**AUC**
CNet	86.24	0.88	0.85	0.86	0.72	0.86
EDT	91.74	0.92	0.92	0.92	0.83	0.92
SVMs	90.83	0.92	0.90	0.91	0.82	0.91
L=14, NF=210, FP=70						
Model	**Acc**	**Sen**	**Spe**	**F-O**	**Kappa**	**AUC**
CNet	93.58	0.92	0.95	0.93	0.87	0.93
EDT	96.33	0.94	0.98	0.96	0.93	0.96
SVMs	89.91	0.88	0.92	0.90	0.80	0.90
L=15, NF=225, FP=75						
Model	**Acc**	**Sen**	**Spe**	**F-O**	**Kappa**	**AUC**
CNet	89.91	0.92	0.88	0.90	0.80	0.90
EDT	89.91	0.94	0.87	0.90	0.80	0.90
SVMs	86.24	0.84	0.88	0.86	0.72	0.86
L=16, NF=240, FP=80						
Model	**Acc**	**Sen**	**Spe**	**F-O**	**Kappa**	**AUC**
CNet	69.72	1.00	0.45	0.62	0.42	0.73
EDT	94.50	0.92	0.97	0.94	0.89	0.94
SVMs	91.74	0.88	0.95	0.91	0.83	0.91
L=17, NF=255, FP=85						
Model	**Acc**	**Sen**	**Spe**	**F-O**	**Kappa**	**AUC**
CNet	93.58	0.94	0.93	0.94	0.87	0.94
EDT	96.33	0.94	0.98	0.96	0.93	0.96
SVMs	88.99	0.86	0.92	0.89	0.78	0.89
L=18, NF=270, FP=90						
Model	**Acc**	**Sen**	**Spe**	**F-O**	**Kappa**	**AUC**
CNet	**92.66**	**0.96**	**0.90**	**0.93**	**0.85**	**0.93**
EDT	**97.25**	**0.96**	**0.98**	**0.97**	**0.94**	**0.97**
SVMs	**92.66**	**0.94**	**0.92**	**0.93**	**0.85**	**0.93**
L=19, NF=285, FP=95						
Model	**Acc**	**Sen**	**Spe**	**F-O**	**Kappa**	**AUC**
CNet	90.83	0.92	0.90	0.91	0.82	0.91
EDT	97.25	0.96	0.98	0.97	0.94	0.97
SVMs	83.49	0.84	0.83	0.84	0.67	0.84
L=20, NF=300, FP=100						
Model	**Acc**	**Sen**	**Spe**	**F-O**	**Kappa**	**AUC**
CNet	91.74	0.92	0.92	0.92	0.83	0.92
EDT	93.58	0.92	0.95	0.93	0.87	0.93
SVMs	91.74	0.90	0.93	0.92	0.83	0.92

L: Level, NF: Number of Feature, FP: Percentage of Feature

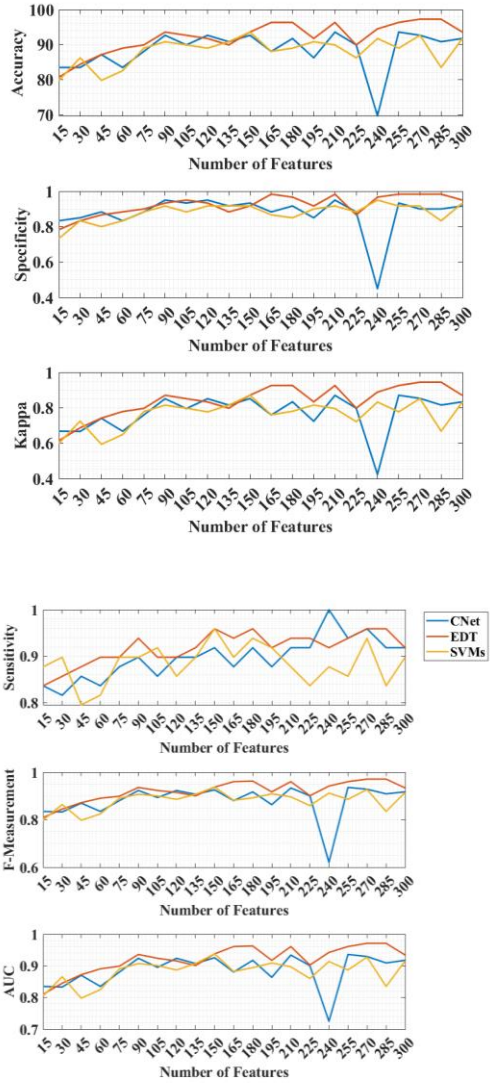

Figure 4 Graphical representation of model performances

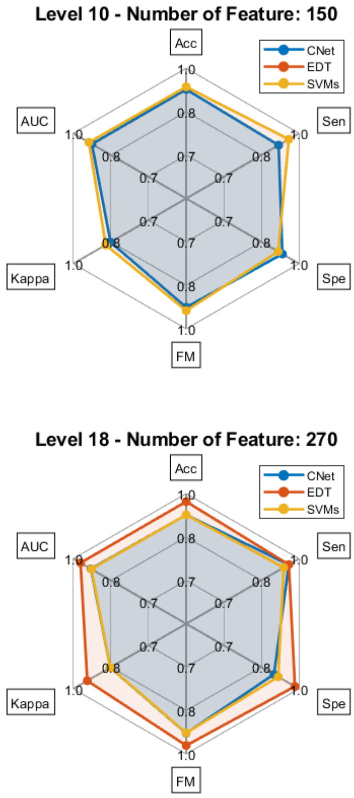

Figure 5 Spider graphical representation of model performances for levels 10 and 18

4. DISCUSSION AND CONCLUSION

Early diagnosis in dermatology is of vital importance for improving the quality of life. There is a need for new, reliable and fast decision support systems that will shorten the diagnostic processes for early diagnosis. New artificial intelligence-based diagnostic techniques that meet the specifications may be developed today. The aim of this study was to develop a fast and reliable decision support system based on artificial intelligence for the detection of Onychomycosis. There are guidelines suggested for image processing processes in the literature [41].

These outlines consist of image, feature extraction, feature selection, and classification steps. The system performance here is directly dependent on the process developed. It has been recently discovered that performances may be increased very well with deep learning methods [33]. With all these developments, interest in the use of deep learning methods has increased. However, the need for high-performance computers for the training of deep learning algorithms is increasing day by day. The interest in classical machine learning still continues due to this disadvantage. In this study, classical machine learning algorithms were preferred considering hardware inadequacies. Considering the applicability of the systems, it is obvious that high-capacity computers cannot exist in every clinic. All image processing processes are done by algorithm in deep learning when classical machine learning algorithms are preferred, deepening should be applied in image processing processes. Digital filters are used to process images in this study. The noise on the image is cleared. In addition to the filters, the images were separated into channel information and different information was produced. Revealing different information that defines the image is thereby aimed. However, having a lot of information does not mean that they are meaningful. Therefore, feature selection algorithms are used to highlight useful information. It is seen in the results that the selected features increase the performance (Table 5.). This increase is an indication of the efficient implementation of the process. The results obtained are compatible with the literature. In addition, the feature selection algorithm helped to increase the performance.

There are studies recommended for the diagnosis of Onychomycosis in the literature [8, 9, 26]. The common feature of these studies is performing deep learning-based classification. Image preprocessing is relatively very less. Images are integrated into the system with their tags. The image processing process is driven by deep learning. Although this process seems relatively adequate, it is quite time consuming for training time. Furthermore, it has a different disadvantage that requiring high level hardware. The most significant advantage of these systems is their high-performance value. The compactness of the model provides a great advantage to the developers [42, 43]. However, non-model development of deep learning processes is possible by an expert developer, like this study.

The performance value of the model proposed in this study is higher than the model results made with deep learning in the literature (Table 6, 7.) [5, 8, 14, 26]. This may be associated with the feature extraction and selection process in image processing. In this study, unlike the literature, high performance is achieved with the help of classical machine learning algorithms instead of deep learning methods. The results obtained are quite good compared to the literature. The image processing process has greatly increased the performance.

Table 6 Comparison of literature results

No	References		Method	Image
1	[14]	Yılmaz 2022	Deep Learning	Microscopic Image
2	[14]	Yılmaz 2022	Specialist Clinician	Microscopic Image
3	[20]	Nijhawan 2017	Deep Learning	Nail Image
4	[24]	Indi 2016	Deep Learning	Nail Image
5	[25]	Kanchna 2021	Deep Learning	Nail Image
6	[5]	Velasquez-Agudelo 2017	KOH-Systematic Compilation	
7	[5]	Velasquez-Agudelo 2017	Histopathology	
8	[26]	Kim 2020	Deep Learning	
9	[26]	Kim 2020	Five Specialist Clinicians	
10	[13]	Han 2018	Deep Learning	
11		**Model Offered**	**Ensemble Decision Tree**	**Nail Image**

Table 7 Comparison of literature results 2

No	Acc	Sen	Spe	F-M	K	AUC	F1	Pre
1	95.90	95.5	97.5			0.991	95.5	95.58
2	72.8	61	95			0.87	74.69	96.3
3	85.11	89.8	89.1		0.848			
4	65							
5	65							
6		61 (44-100)	95 (75-100)					
7		84 (61-93	89 (44-100)					
8		70.2	72.7					
9		73	49.7					
10		87.2-96.7	69.3-96.7			0.82-0.98		
11	**97.25**	**96**	**98**	**0.97**	**0.94**	**0.97**		

: F-Measurement, AUC: Area Under the Receiver Operating Characteristic (ROC) Curve, Acc Accuracy, Sen Sensitivity, Spe Specificity, Pre Precision, K Kappa, F1 F1-Score

After onychomycosis formation on the nail, pigments of different colors begin to form in the nail. This an important point for diagnosis. A study conducted in 2022 developed an onychomycosis diagnosis algorithm with deep learning methods based on changes in nail pigments [40]. The achievement rate of the system was evaluated over the pigment-based estimation. The most important limitation of the study is that the performance values given are not comparable with other studies in the literature. All the results given in this study have been evaluated from different perspectives so that they can be compared with the literature. The results obtained are better than the literature. This may be because the image processing process is done effectively.

Researches on artificial intelligence in different methods continue for the diagnosis of onychomycosis [44, 45]. Methods considered as new research topics are Nail Dermoscopy (Onychoscopy), Reflectance Confocal Microscopy and Molecular Assays. The developed methods are still being investigated in the literature and their sensitivity varies between 52.9% and 100%. This change in sensitivity still indicates that research needs to continue.

It is an inevitable fact that the development of artificial intelligence-supported diagnostic processes in dermatology will facilitate the work of dermatologists. As the society, dermatologists and developers may adapt to this process faster, the diagnosis and treatment times will be shorter. Therefore, artificial intelligence studies in dermatology have started to have a vital importance. Further studies are important building blocks needed for systems to become perfect.

This study is one of the artificial intelligence applications in dermatology. The proposed method for the detection of Onychomycosis in the study is different and better than the literature in terms of performance and procedure steps. The significant advantages of the study may be listed as follows. 1. Conventional machine learning algorithms were preferred instead of deep learning, and the training period was shortened. 2. More detailed information about the images is revealed along with the advanced image processing process. 3. The relevant information of the images is selected through the help of feature selection algorithms. Significant improvements were thereby achieved in training duration and performance. 4. The performance value of the models proposed in this study has a higher accuracy rate compared to the literature. 5. The model developed is adequate to work on all kinds of platforms. When all these advantages are considered in general, it is evaluated that the proposed model may help the dermatologist as a decision support system in the clinic.

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The Declaration of Research and Publication Ethics
The authors of the paper declare that they comply with the scientific, ethical and quotation rules of SAUJS in all processes of the paper and that they do not make any falsification on the data collected. In addition, they declare that Sakarya University Journal of Science and its editorial board have no responsibility for any ethical violations that may be encountered, and that this study has not been evaluated in any academic publication environment other than Sakarya University Journal of Science.

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