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DETECTION OF NAIL DISEASES USING ENSEMBLE MODEL BASED ON MAJORITY VOTING

ÇOĞUNLUK OYUNA DAYALI TOPLULUK MODELİ İLE TIRNAK HASTALIKLARININ TESPİTİ

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ABSTRACT

Nail diseases are disorders that can have serious effects on human quality of life. With the developing computational methods and technology, anomalies on the nail may be detected quickly and in a non-invasive way. This study proposes a model that provides better performance by combining the results of different deep learning networks with the ensemble learning method. The performance of 7 different deep learning architectures was examined using a database containing 17 disease classes. The proposed method achieved 75 % accuracy, resulting in significant increases in precision and recall metrics compared to individual deep-learning architectures. Thanks to a mobile application that will be developed, the proposed model for large-scale screening may be used as an assistive decision support system for medical professionals. When the results are observed, we predict that early detection of nail diseases (in a remote way) on the hand, which is one of our most used limbs, can reduce hospital visits and costs. In addition, the proposed method can be integrated into dermatoscopy devices used for skin diseases and mole analysis.

Keywords: Deep learning, telehealth, nail diseases, majority voting, ensemble learning

ÖZET

Tırnak hastalıkları, insanın yaşam kalitesini ciddi şekilde etkileyebilen bozukluklardır. Gelişen hesaplamalı yöntemler ve teknoloji ile tırnaktaki anomaliler hızlı ve girişimsiz bir şekilde tespit edilebilmektedir. Bu çalışma, farklı derin öğrenme ağlarının sonuçlarını topluluk öğrenme yöntemiyle birleştirerek daha iyi performans sağlayan bir model önermektedir. 7 farklı derin öğrenme mimarisinin performansı, 17 hastalık sınıfı içeren bir veritabanı kullanılarak incelenmiştir. Önerilen yöntem % 75 doğruluk elde etti ve bireysel derin öğrenme mimarilerine kıyasla kesinlik ve duyarlılık metriklerinde önemli artışlar sağladı. Önerilen model geliştirilebilecek bir mobil uygulama sayesinde, büyük ölçekli taramalarda tıp profesyonelleri için yardımcı bir karar destek sistemi olarak kullanılabilecektir. Sonuçlara bakıldığında en çok kullandığımız uzuvlarımızdan biri olan eldeki tırnaklarımızda meydana gelen hastalıkların (uzaktan) erken tespit edilmesinin hastane ziyaretlerini ve maliyetleri azaltabileceğini öngörüyoruz. Ayrıca önerilen yöntem cilt hastalıkları ve ben analizi için kullanılan dermatoskopi cihazlarına entegre edilebilir.

Anahtar Kelimeler: Derin öğrenme, tele sağlık, tırnak hastalıkları, çoğunluk oylaması, topluluk modeli

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INTRODUCTION

Early disease detection plays an important role in improving the quality of life. In the field of public health, there are different ways to diagnose diverse diseases in the human body. Many of the conditions can be detected by observing symptoms such as the variation in the pigmentation, appearance, size, and structure of the nail (Nijhawan et al., 2017). Minor changes in the nails may be overlooked as a result of the examination by specialists, and these changes can have painful consequences in the long run. It can negatively affect a person's quality of life and activities (Chelidze & Lipner, 2018). With the development of artificial intelligence, deep learning and computer vision-based techniques are used for early disease diagnosis (Mehra et al., 2021). These techniques include image processing technologies and algorithms in the deep learning area (Abdulhadi et al., 2021). Deep learning and machine learning have brought many benefits in the field of dermatology in detecting diseases (Azad et al., 2021).

Our preliminary study on nail diseases is presented in Yamaç et al. (2022). In this manuscript, to summarize, more disease classes and images were used, more deep learning networks were employed, an innovative method based on majority voting was proposed to the related field, and to make deep learning networks explainable the related examples were shown. In this work, different deep-learning models were used to classify and identify nail diseases using an ensemble model based on majority voting. In our study, 17 nail diseases were detected. Darier's disease, Muehrcke's lines, Alopecia areata, Beau's lines, Bluish nail, Clubbing, Eczema, Half and half nails (Lindsay's nails), Koilonychia, Leukonychia, Onycholysis, Red lunula, Pale nail, Splinter hemorrhage, Terry's nail, White nail, Yellow nails are the names of the detected diseases. Shape or growth changes in nails are common symptoms of Clubbing, Koilonychia, Onycholysis, Beau's lines, and Yellow nail diseases (Fawcett et al., 2004). As a result of Terry's nails, Half and half nails, Muehrcke's lines, and Splinter hemorrhage diseases, color changes may occur in the nails. Raynaud's disease can be detected from the symptoms of Beau's lines, Koilonychia, and Yellow nails diseases (Fawcett et al., 2004). Lack of oxygen has been stated as the reason for the blue color of the nails. In addition, this disease can cause lung infection (Pandit & Shah, 2013). The most common symptoms of Alopecia areata are small pits on the nail and the occurrence of trachyonychia (Chelidze & Lipner, 2018). Terry's nails occur in the vast majority of patients diagnosed with cirrhosis of the liver. It is stated that the nail layer on Terry's nail is whitish with a tight pink line (Safira et al., 2019). Onycholysis disease occurs when the nail layer is separated from the nail bed, and this is generally originated from a trauma. White discoloration occurs in the area of trauma (Fawcett et al., 2004).

RELATED WORKS

The work of Indi and Gunge (2016), constructed a decision tree using the C4.5 algorithm and a color detection approach. An accuracy rate of 65 % was achieved. The main aim of the study was to compare the performances of classifier models used in the prediction of five nail diseases.

Nijhawan et al. (2017), in their study, the use of various classification models such as a k-nearest neighbor (k-NN), random forest, support vector machine (SVM), and convolutional neural network (CNN) was tested for best performance. A deep learning approach was designed to identify eleven nail diseases. The employed dataset consists of 4190 images. CNN (in a hybrid way) was used for feature extraction in this study. The most successful result was achieved with the CNN model with 80.45 %.

In the work of Safira et al. (2019), performed feature extraction using a gray-level co-occurrence matrix (GLCM) and classification utilizing k-NN. This research aims to identify abnormalities in the so-called Terry's nails. They tested image classification systems by converting images from RGB to grayscale. Dataset was divided into two classes as healthy nails and Terry's nails. 60 % of the data was employed for training and 40 % of the data was employed for testing. 5 different tests were performed for the dataset.

In their study, Mehra et al. (2021), 4 of the CNN deep learning models were tested. The VGG16 method was the best-performing method. An accuracy of 92 % was obtained. Healthy nails, subungual melanoma, and yellow nail syndrome were detected. A total of 1040 images were used.

In the work of Thahira Banu and Devi (2021), GLCM with a filter-based approach was used for feature extraction. A new hybrid method was used for classification combining k-NN and SVM models. In this study, 8 nail abnormalities were detected and 480 nail images were used. 70 % of the data was utilized for training and 30 % of the data for testing. Classification accuracy was 71.11 % with the SVM algorithm and 80.26 % with the k-NN algorithm. When hybrid classification was performed, it was shown that it provides 98.55 % overall accuracy.

In their study, Begum et al. (2021), a transfer learning approach was implemented using the MobileNetV2 model. The dataset consists of 2500 images at first, then it was expanded to 7500 images. Using the deep learning method, 4 skin diseases and 2 nail diseases were detected. An accuracy of 92.50 % was reached and an application named "DermaDoc" was developed.

Yani (2019) used CNN for the identification of Terry's nail disease. Healthy and Terry's nails were detected. In this study, 95.24 % accuracy was obtained with the transfer learning method using the Inception-V3 model. It was stated that 115 of the images which belong to Terry's nail class were obtained from Google images, and 100 of the images which belong to the healthy nail class were obtained from Telkom University.

The work of Sah et al. (2019), used the deep learning model VGG16 in their study. This model has been applied to classify 10 dermatological diseases in total, including nail fungus and nail wart diseases. 5500 images were obtained from the Dermnet dataset. In this study, the highest accuracy was obtained as 76.30 %.

In their study, Abdulhadi et al. (2021), five deep-learning approaches were used to detect nail disorders. 92 healthy, 73 nail hyper-pigmentation, 60 nail Clubbing, and 55 nail fungus pictures were utilized. In this study, the highest accuracy was obtained with the ResNet50 and DenseNet201 architectures as 96.39 %.

MATERIAL AND METHODS

Transfer Learning-Based Models

Transfer learning (TL) is the use of knowledge of a previously trained model for a different problem. Training a deep architecture from scratch is practically difficult. TL provides a promising option that takes advantage of a pre-trained model which was already trained by a larger database (Shao et al., 2018).

Deep learning models need large datasets. This is the main reason why TL is preferred. With small amounts of data, successful deep-learning studies can be carried out by using the knowledge of the model that was previously trained with large datasets. In this approach, all layers of the deep model are utilized with pre-trained parameters, without including the last fully connected (FC) stages (Tandel et al., 2021). In these stages, the information is readily used. This process is carried out by the freezing method.

VGG16, ResNet, and DenseNet models are popular deep learning algorithms that are often preferred. In this work, deep learning models trained with the ImageNet dataset were used. The employed architectures in this study are mentioned below.

MobileNet

It is known as a lightweight CNN. This is one of the most useful architectures for mobile applications. This method significantly reduces the number of parameters. It also provides a high speed in training by employing depth-wise separable convolutions (Chowdary et al., 2021). Also, it is one of the first mobile application models of Tensorflow. In our study, in addition to MobileNet, MobileNetV2, the second version, was also employed.

DenseNet

It is a recently recommended densely connected CNN. This network contains 4 dense blocks and is less prone to overfitting (Rahman & Dola, 2021). DenseNet169 and DenseNet121 models were preferred in our study.

VGG-16

It is also called OxfordNet and takes its name from the first letters of the Visual Geometry Group. It contains only convolution and pooling layers. In all its layers, the kernel size is 3x3, the pool size is 2x2. It contains a total of 16 convolution layers and 138 million parameters (Theckedath & Sedamkar, 2020).

ResNet

It is known as a deep residual network. Based on the VGG-19 architecture, the ResNet network uses 34 layers of flat network architecture with fewer filters and lower complexity than VGG networks (Barsha et al., 2021). ResNet101V2 and ResNet50V2 were used in this work.

Proposed Ensemble Model

In our study, an ensemble model based on the majority voting method was proposed. Majority voting is an ensemble method that creates multiple models and then combines them to produce better results.

There are two main approaches: hard voting and soft voting. In the first approach, each model votes for each test sample, and the final output that gets more than half of the votes is selected. If none of the predictions receives more than half of the votes, it is assumed that this approach may not make useful predictions (Akcan ve Sertbaş, 2021). In the second approach, each classifier gives a probability output that a particular test sample belongs to a target group. Estimations are weighted and aggregated by the importance of the learner. The target class with the most weighted probability sum is the winner of the voting (Taha & Malebary, 2022).

Utilizing a single model may not always provide a high level of accuracy and may be subject to overfitting. Because each model has superior and weak properties related to classification tasks. Majority voting is employed to increase the strength of individual classifiers and reduce their weaknesses (Akcan ve Sertbaş, 2021).

PERFORMANCE EVALUATION

In the ensemble models, it is generally preferred that the number of models is odd. Otherwise, two or more of the voted classes may be equal. In this work, the seven most popular and successful deep learning models were used. As a result of the predictions made by 7 different deep learning models for the test dataset, the most voted class was selected for each image. The visual representation of the proposed model can be observed in Figure 1.

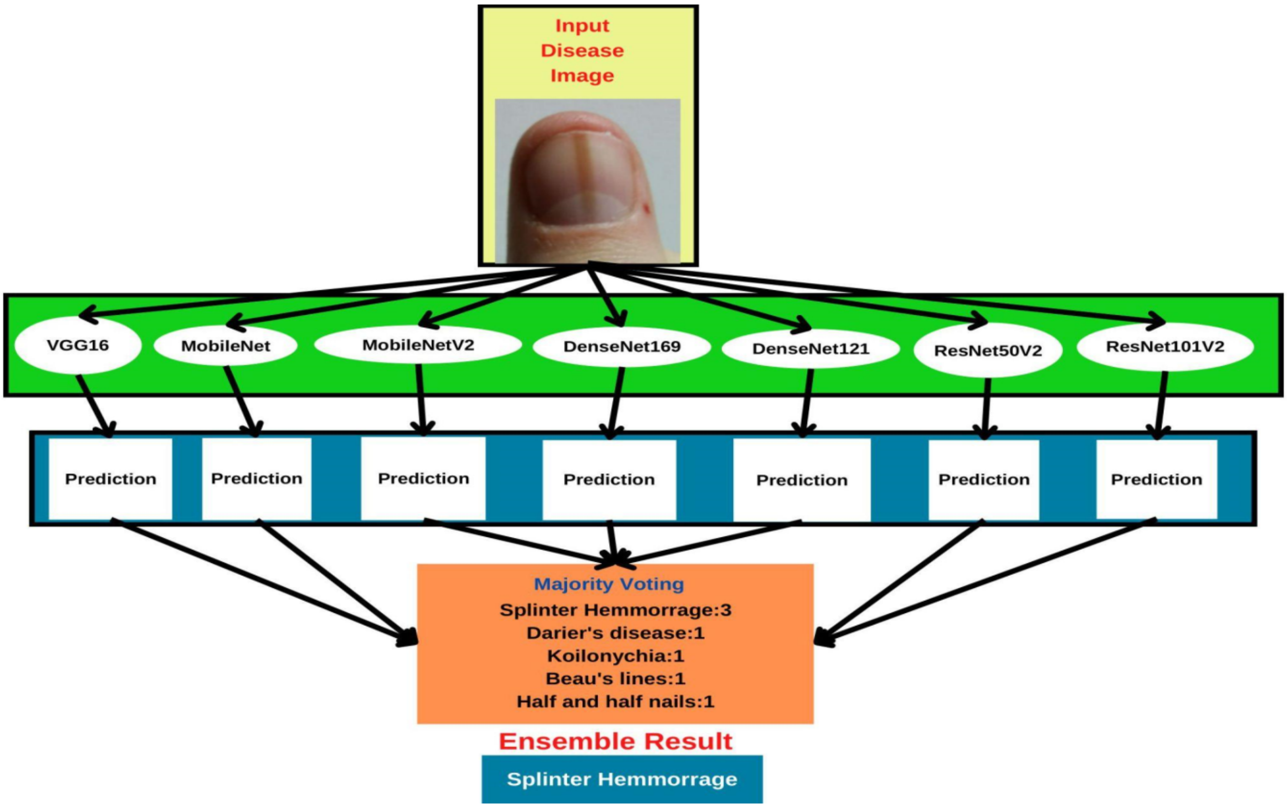

Figure 1. Majority Voting Based Proposed Ensemble Model

Dataset

Dataset is one of the vital inputs in deep learning works. The size of the dataset is the factor that directly affects accuracy. While looking for a dataset on nail diseases, we observed that most of the datasets were inadequate in size. In this study, a dataset containing 17 nail disease classes was preferred due to the high number of class varieties (Reubenindustrustech, 2022). It includes 655 images. The dimensions of the images are in the range of 23x47 and 594x471 showing variety in resolution. All images located in the dataset are in PNG format. The number of images for each class is as follows: Alopecia areata 47, Beau’s lines 42, Bluish nail 50, Clubbing 40, Darier’s disease 47, Eczema 45, Half and half nails 38, Koilonychia 38, Leukonychia 31, Muehrcke's lines 33, Onycholysis 50, Pale nail 35, Red lunula 15, Splinter hemorrhage 62, Terry's nail 36, White nail 19, Yellow nails 27.

Implementation Details and Training Procedure

Before the training of our models, images of different sizes were resized as 128x128x3 to be given to the model. Then, the dataset was split into two groups: train (80 % of the dataset) and test (20 % of the dataset) groups. As a result of the splitting process, the dataset was formed as 524 train and 131 test images. Then, the data augmentation method (given in the next subsection) was applied to temporarily extend the number of images only in the training set and to enable the model to learn better. Tesla T4 GPU provided by Google Colab was used for the training.

Data Augmentation

This method enables the creation of processed synthetic copies by applying various operations to the audio, image, and text data in the preprocessing stage, and adding these copies to the existing training dataset to form a large training dataset. Although deep learning methods have led to successful results in many areas in recent years, it also brings a hunger for data (Summers & Dinneen, 2019). In cases where the training dataset is not sufficient, we will inevitably encounter an overfitting problem. In order to reduce this effect, labeled training examples can be increased by applying various operations to the images with data augmentation (Stivaktakis et al., 2019). These transformations may contain noise addition, rescaling, rotating, vertical and horizontal flips, etc. The new copies obtained as a result of these transformations are integrated into the training dataset. In this study, we used 7 different data augmentation approaches (rotation, shearing, horizontal shift, vertical shift, horizontal flip, zoom, and padding) due to the insufficiency of the dataset. In this way, the training dataset (524 images) has been temporarily increased to 7 times. Thus, before the training process, the training dataset was increased to 3668 images.

Hyperparameter Optimization

Hyperparameter optimization is the process of determining the hyperparameters that show the best success in the set of metric values while building the model.

Table 1. The Hyperparameter Values And Accuracy Of The Proposed Majority Voting Algorithm

Number of Epochs	Learning Rate	Batch Size	Number of Neurons	Accuracy
50	0.001	32	100	0.63
30	0.0001	4	512	0.73
30	0.0001	8	512	0.73
25	0.0001	4	512	0.73
25	0.0001	8	512	**0.75**
25	0.0001	8	1024	0.69
20	0.001	8	512	0.70
20	0.0001	4	512	0.69

When constructing a convolutional neural network structure, hyperparameters such as the number of convolution layers, epochs, batch size, learning rate, and the number of fully connected layers directly affect the success of our model. For this reason, it is of great importance to determine the values that will make the model most successful (Gülcü & Kuş, 2019). For hyperparameter optimization, we used the GridSearchCV method in this study. This algorithm builds models with all combinations for the hyperparameters and their values to be optimized and returns the most successful hyperparameter values according to the specified metric. In this study, the accuracy value of the majority voting algorithm was compared while determining the most appropriate hyperparameter values. The optimized values are the number of epochs, batch size, learning rate, and neurons of the added fully connected layers. In Table 1, the hyperparameter values that make the majority voting algorithm the most successful are given. When

Table 1 is examined, the hyperparameter values that make the proposed ensemble model the most successful with an accuracy rate of 75 % are in the fifth row.

Performance Comparison and Experimental Results

The average accuracy with F1-score, precision, and recall rates per class is given in Table 2.

Table 2. Performance Of The Proposed Algorithm Per Classes

Classes	Precision	Recall	F1-Score
Darier's Disease	0.82	1.00	0.90
Muehrcke's Lines	1.00	0.71	0.83
Alopecia Areata	0.78	0.78	0.78
Beau's Lines	0.45	0.62	0.53
Bluish Nail	0.80	0.80	0.80
Clubbing	0.88	0.88	0.88
Eczema	0.69	1.00	0.82
Half and Half Nail	1.00	0.62	0.77
Koilonycia	1.00	0.38	0.55
Leukonycia	0.57	0.67	0.62
Onycholysis	0.60	0.60	0.60
Pale Nail	0.86	0.86	0.86
Red Lunula	1.00	1.00	1.00
Splinter Hemorrhage	0.71	0.92	0.80
Terry's Nail	0.67	0.57	0.62
White Nail	1.00	0.50	0.67
Yellow Nail	0.75	0.60	0.67
Performance Metrics			
Accuracy			0.75
Weighted Average	0.78	0.75	0.74

While the proposed method achieved the most successful results in the Red Lunula class, the least successful results (in terms of F1-score) were observed in Beau's Lines class in Table 2. The average accuracy for 17 classes was found to be 75 % in Table 2.

In Table 3, the proposed majority voting-based approach is compared to 7 state-of-the-art architectures in terms of accuracy, precision, and recall metrics. It is seen that the proposed method outperforms all the architectures in each metric. When other methods are examined, it is seen that DenseNet169 is the second most successful architecture in terms of accuracy, and VGG16 is the architecture with the lowest performance. This is also seen in the accuracy graph in Figure 2 and the loss graph in Figure 3 of the trained models. With the training of seven different CNN models separately, the total training time took approximately 10 minutes.

Table 3. Performance Of The Proposed Algorithm With State-Of-The-Art Deep Learning Approaches

Model	Precision	Recall	Accuracy
VGG16	0.46	0.43	0.47
MobileNet	0.65	0.58	0.59
MobileNetV2	0.64	0.60	0.61
DenseNet169	0.73	0.71	0.70
DenseNet121	0.70	0.62	0.63
ResNet50V2	0.63	0.58	0.59
ResNet101V2	0.63	0.55	0.56
Majority Voting	**0.80**	**0.74**	**0.75**

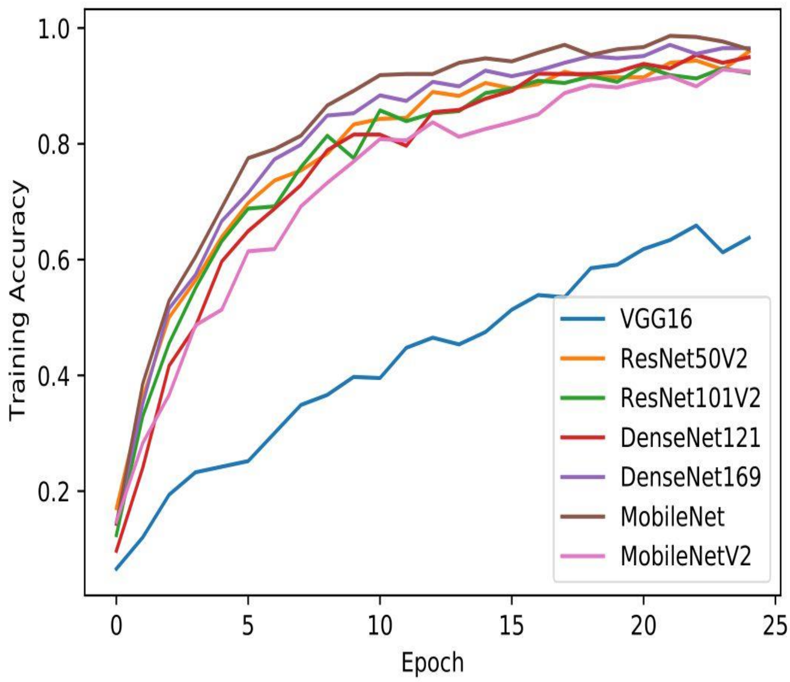

Figure 2. Training Accuracy Graph For All Models

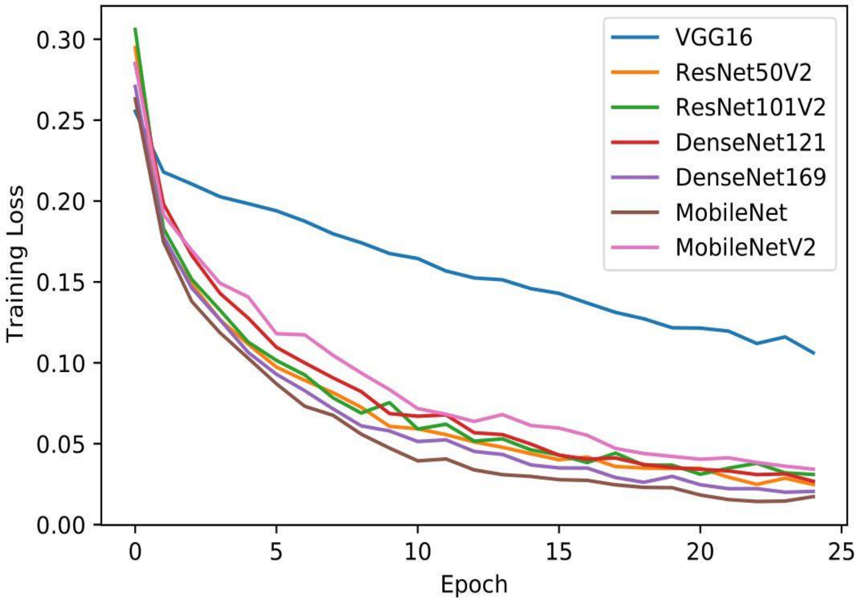

Figure 3. Training Loss Graph For All Models

In Figure 4, the confusion matrix for the proposed ensemble model is given. It can be concluded that Koilonycia and White Nail classes are the most confused classes while Red Lunula and Darier's Disease are the easily classified classes.

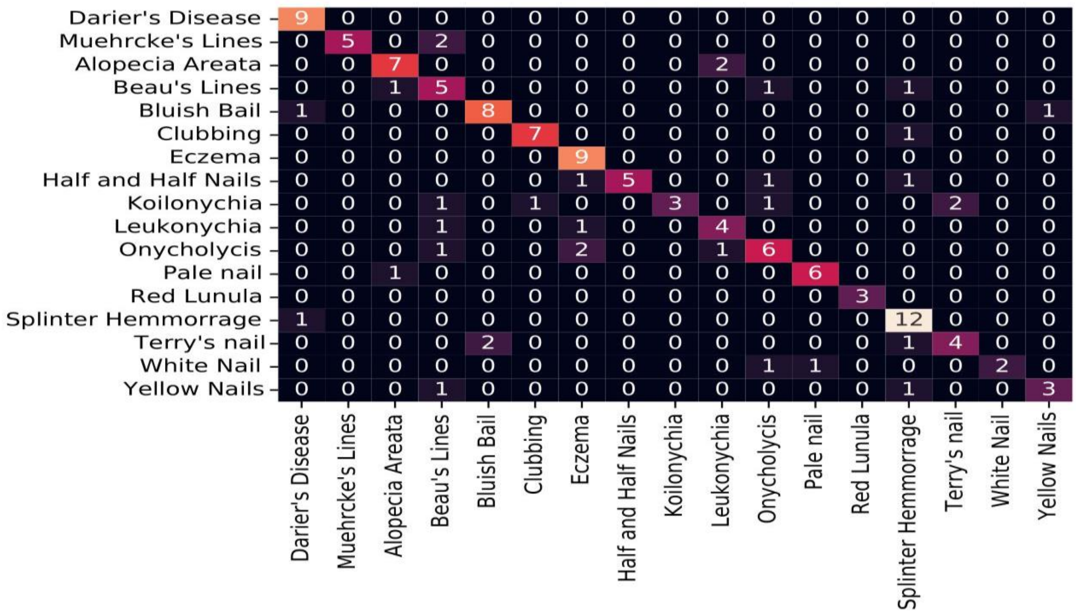

Figure 4. Confusion Matrix For The Proposed Ensemble Model Based On Majority Voting Algorithm

DISCUSSION

Using 7 different deep transfer learning methods, 17 nail diseases were analyzed. More accurate detection of 17 nail diseases will be very beneficial to both the field of dermatology and public health. It will positively affect people's health status and quality of life. There are studies in the literature that use their own database and have a smaller number of disease classes. In the related works section, studies on nail disease detection were summarized. Considering the studies by the number of diseases, the work of Nijhawan et al. (2017) (at most in 11 classes) achieved an accuracy of 80.45 %. Although the databases and disease types used are different, in order to compare this study with ours, we randomly reduced the number of disease classes to 11. Our dataset was reduced to 495 images. We achieved an 81 % success rate with the proposed majority voting method. A direct comparison could not be made as each study reported results on a different database and a different number/type of nail diseases. Therefore, the performance of the state-of-the-art deep learning methods and the method we propose were compared. One can conclude that a significant improvement in the performance of the nail disease classification problem has been achieved with the proposed approach. In recent years, as the number of images increased, we observe that deep learning methods come to the forefront compared to classical machine learning methods.

Although each individual deep model doesn't give satisfactory results, it was aimed to increase success by creating an ensemble model with the majority voting approach. In recent years, we have seen that ensemble learning has increased performance in various fields (Ocal & Barisci, 2022; Taha & Malebary, 2022; Sünnetci & Alkan, 2022b, 2022a; Ilhan et al., 2022; Tandel et al., 2021; Barsha et al., 2021; Solmaz et al., 2020; Sadaei et al., 2019).

Being interpretable is a very important feature of a deep learning model. Gradient-based sensitivity analysis method (Grad-CAM) can be used to visualize the classification output and produce an explainable heatmap (Jiang et al., 2020). These heatmaps help us to explore visually which parts of the image our model is making predictions based on and help anyone to validate the model. The produced heatmap is initially equal in size to the feature maps in the last layer of the encoder. But later it is scaled up to the input image size. The Relu function is used in feature maps to reveal effective information about the class of interest (Xiaou et al., 2021). In Figure 5, example images and their obtained heatmaps are visualized. The regions close to the red color in the heatmap are the regions that our model focuses on when making its predictions. When we examine these images, we can say that the deep learning model concentrates on the anomaly regions and is able to detect these regions.

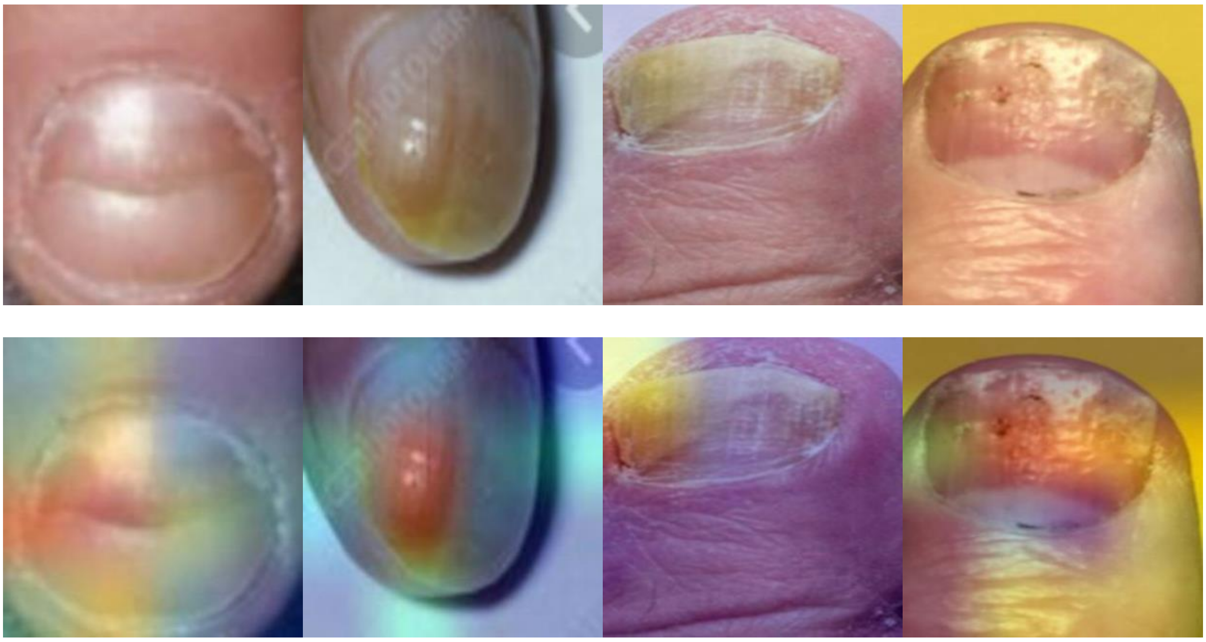

Figure 5. Sample Images (Upper Row) and Their Related Heatmap Representation (Bottom Row)

CONCLUSION

In this work, we have proposed a supervised deep neural network that will facilitate the detection of 17 different nail diseases with the majority voting approach, by using the transfer learning method and the knowledge of different deep learning models. Throughout this work, we used accuracy as a success metric. In order to achieve the maximum accuracy value, we found the parameters with hyperparameter optimization. With the help of hyperparameter optimization, we compared the individual deep learning methods with the model we proposed and validated it visually. Although a direct comparison is not possible since the related studies in the literature were conducted on fewer classes and different databases, in this study, a successful ensemble model comparable to the literature was proposed, which surpasses the individual performance of state-of-the-art deep learning models on a more comprehensive database.

As a limitation of the study, the datasets of nail diseases are quite inadequate in size. If the dataset is large enough, the model learns the different features of different classes readily, and the probability of making successful predictions during the classification phase increases. For this reason, open-source datasets on nail diseases could be increased in terms of the number of images.

From a future perspective, we intend to build a mobile application that can be used by healthcare professionals and the public free of charge and that can help to detect many nail diseases in a remote and non-invasive way.

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