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HUMAN NAIL DISEASES CLASSIFICATION BASED ON TRANSFER LEARNING

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Abstract. *Diseases of human nails are a kind of deformities in nails. Nail has its own various class of diseases, which have their own set of symptoms, signs, causes and effects that may or may not impute to other medical conditions. In this study, four types of nail diseases have been addressed, represented by healthy nail, nail hyperpigmentation, nail clubbing and nail fungus. The images resulting from these nail diseases are classified using five pre-trained models of deep Convolutional Neural Network (CNN), namely (AlexNet, Vgg16, GoogleNet, ResNet50 and DenseNet201). Six metrics are calculated to evaluate the performance of each Transfer Learning (TL) model, which are accuracy, recall, specificity, precision, F-score and time. The TL models are implemented and trained based on MATLAB programming software. The dataset has been tested and the accuracy of each case has been reported. The accuracies based on AlexNet, Vgg16, and GoogleNet are 92.5%, 87.5%, 93.98%, while that based on ResNet50 and DenseNet201 has accuracy of 96.39%.*
Keywords: CNN, Transfer learning, Pre-trained model, AlexNet, DenseNet201, Nail diseases

1. **Introduction.** In healthcare domain, many diseases can be predicted by observing color and shape of human nails. A white spot here, a rosy stain there, or some winkle or projection may be an indication of disease in the body. Problems in the liver, lungs, and heart can show up in your nails. Doctors observe nails of patient to get assistance in disease identification [1]. Usually, pink nails indicate healthy human. Healthy nails are smooth and consistent in color. Anything else affecting the growth and appearance of the fingernails or toenails may indicate an abnormality. A person's nails can say a lot about their health condition. The need of such systems to analyze nails for disease prediction is because human eye is having subjectivity about colors, having limitation of resolution and small amount of color change in few pixels on nail not being highlighted to human eyes which may lead to wrong result, whereas computer recognizes small color changes on nail.

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Figure 1. The main parts of the nail

Figure 1 shows the nail parts. It is clear from the figure that the nail consists of four parts represented by Lunula, Cuticle, Nail Root and Nail Plate. The Lunula part is the moon shape observed at the base of the nail plate, Cuticle is a layer of clear skin located along the bottom edge of the finger, the Nail Root portion lies below the skin, underneath the nail, and extends several millimeters into the finger, and the Nail Plate is the hard part of the nail, made of translucent keratin and it is characterized by smooth, curved and light pink in color. It is the visible part of the nail [2].

Image processing techniques and algorithms have played a vital role in many applications [3-6]. However, these techniques showed direct impact in serving the human being in the medical sense. The early detection and diagnosis of many diseases have saved millions of people by virtue of advances in image processing methodologies and technologies [7,8]. The dermatology is a field of medical science that has recently attracted the attention of the researchers. Image matching algorithms for automated melanoma screening, skin cancer detection, categorization of dermatological images, and dermatological disease detection are some of the newly pursued areas [9].

Deep Learning (DL) is part of machine learning in artificial intelligence. The structure of DL consists of Artificial Neural Networks (ANNs), which are capable of unsupervised learning of unlabeled and unstructured data. The DL uses ANN architectures that contain a quite large number of processing layers, as opposed to "shallower" architectures of most traditional ANN structures. The main advantage of DL is the ability to exploit directly raw data without using hand-crafted features [10,11].

In this study five models of transfer learning based Convolutional Neural Network (CNN) were used to classify finger nail diseases and compare the results between the used models. The term transfer learning refers to the process of transfer knowledge from previous training to be used in new research so that training time will be completed faster. This is certainly different from the process of training on traditional machines that learn input data from the beginning and require very long computational time [12].

In this work four types of nail diseases have been classified (healthy nail, hyperpigmentation, nail clubbing, and nail fungus). Figure 2 shows the images of the used nail diseases types.

The most important features in nail images have been used and trained to detect diseases, which are beyond the cause of the shapes and colors in the human nail. Figure 2(a) shows the image of a healthy human nail, no change in the natural shape or color that refers to any disease. Figure 2(b) shows the nail hyperpigmentation. This type of color changing in nails is caused by many reasons. Nail hyperpigmentation may occur because of physiologic causes including racial melanonychia and pregnancy. Other reasons may

Figure 2. Examples of nail diseases images: (a) healthy nail, (b) hyperpigmentation, (c) nail clubbing, and (d) nail fungus

cause nail hyperpigmentation including chronic radiation dermatitis, basal cell carcinoma and chronic radiation dermatitis [13]. AIDS also may cause nail hyperpigmentation.

Figure 2(c) shows nail clubbing. Nail clubbing may occur due to many diseases, including hemiplegia, vascular lesions, neoplastic and liver diseases [14]. The last nail diseases type classified in this paper is shown in Figure 2(d). Differential diagnoses of nail fungus include traumatic onycholysis (usually symmetrical and subungual hyperkeratosis is absent) and nail psoriasis (diffuse hyperkeratosis, several/all toenail involved, others skin and nail signs of psoriasis) [15].

This paper made contributions as listed below:

- Comparison between five models of TL, namely AlexNet, Vgg16, GoogleNet, ResNet50 and DenseNet201.
- Choose four classes of human nail images for classifying, the first class is the normal nail and the rest three classes are for important and dangerous nail shapes, namely nail hyperpigmentation, nail clubbing and nail fugus.
- Collect the nail images for training due to the lack of a special dataset for nail diseases.

The paper is ordered as follows: Section 1 for introduction, Section 2 for literature survey, Section 3 for methodology, Section 4 for collection of data, Section 5 for results and discussion and finally, conclusion and future work in Section 6.

2. **Literature Survey.** There are some existing researches in this field of human nail diseases classification that uses different algorithms. This section discussed briefly the various researches associated with this work. Sharma and Ramaiya [16] presented Nail Color and Tecture Analysis for disease detection. This system used an algorithm which extracts the area of the nail automatically and check this nail part for disease classification based on nail texture and color.

Another paper for nail disease detection is proposed by Nithya et al. [17]. The proposed system is also getting the color feature of the nail image and then the system will check the specific disease. Nijhawan et al. [9] developed an approach based on deep learning for nail diseases identification. They proposed a novel deep learning framework for detection and classification of nail diseases from images. The novel algorithm uses a hybrid of Convolutional Neural Networks (CNNs) for feature extraction. The system accuracy reached 84.58%.

Yani et al. [12] proposed an "Application of Transfer Learning Using Convolutional Neural Network Method for Early Detection of Terr's Nail". In this research the authors used a transfer learning model, namely TensorFlow Inception-V3. The system achieved 95.24% accuracy. Indi and Patil [18] developed a system for nail diseases classification based on several techniques such as SVM classifier, KNN classifier and ANN classification. The system gave 65% accuracy. Rahman et al. in [19] developed a leukonychia nail diseases detection system using deep learning approach. This research uses three TL models: Vgg16, Vgg19 and INCEPTION-V3 for features extraction. The results have 93.8% correctness. This research made a comparison among 5 TL models and chose 3 of more dangerous classes of nail diseases for detection.

3. Methodology.

This section describes the algorithms used in this research. The transfer learning-based CNN has been applied to classifying the nail diseases and this study concentrates on finding the most appropriate pre-trained CNN model. This section is divided into 3 sub-sections: transfer learning concept, CNN pre-trained models and performance evaluation.

3.1. Transfer learning concept.

The CNN algorithms are typically applied on a big dataset rather than a small one. Transfer learning concept can be useful for these applications where a small dataset is available. The concept of transfer learning is shown in Figure 3, where the trained model that is used on a larger data can be used on a small data and get a good result. Recently, the transfer learning method has been successfully applied in various fields such as medical image classification, manufacturing and baggage screening [20].

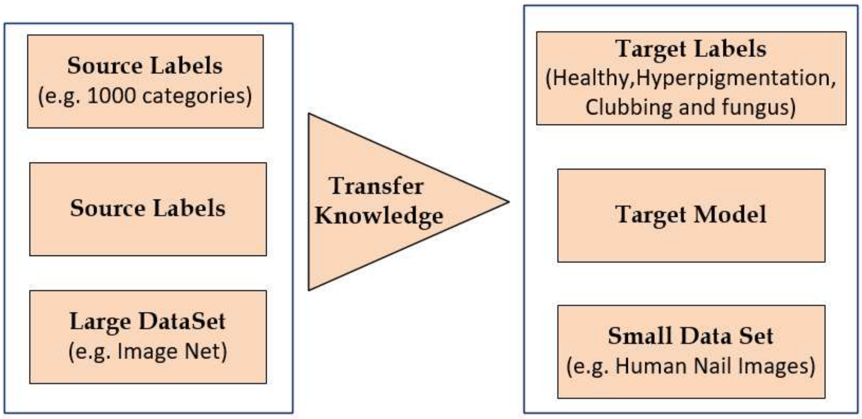


FIGURE 3. Transfer learning concept

3.2. CNN pre-trained models.

In this study, five pre-trained deep CNNs models are used for human nail diseases classification: AlexNet [20], Vgg16 [21], GoogleNet [21], ResNet50 [22] and DenseNet201 [23]. A brief explanation for these models is mentioned below.

3.2.1. *AlexNet.* AlexNet was proposed by Rahman et al. [20]. AlexNet had the ability to classify more than 1000 different classes using deep layers of 650K neurons and 60 million parameters. This network consists of five Convolutional Layers (CLs) with three pooling layers, two Fully-Connected Layers (FLCs) and a softmax layer [24]. The network architecture is shown in Figure 4.

3.2.2. *Vgg16.* Vgg16 is a CNN model that is trained on more than a million images from ImageNet dataset [25]. The network having 16 deep layers can classify images up to 1000 classes. This network has rich feature representations for a wide range of images and the input image size is $224 \times 224 \times 3$ [24]. Figure 5 shows the model architecture of Vgg16.

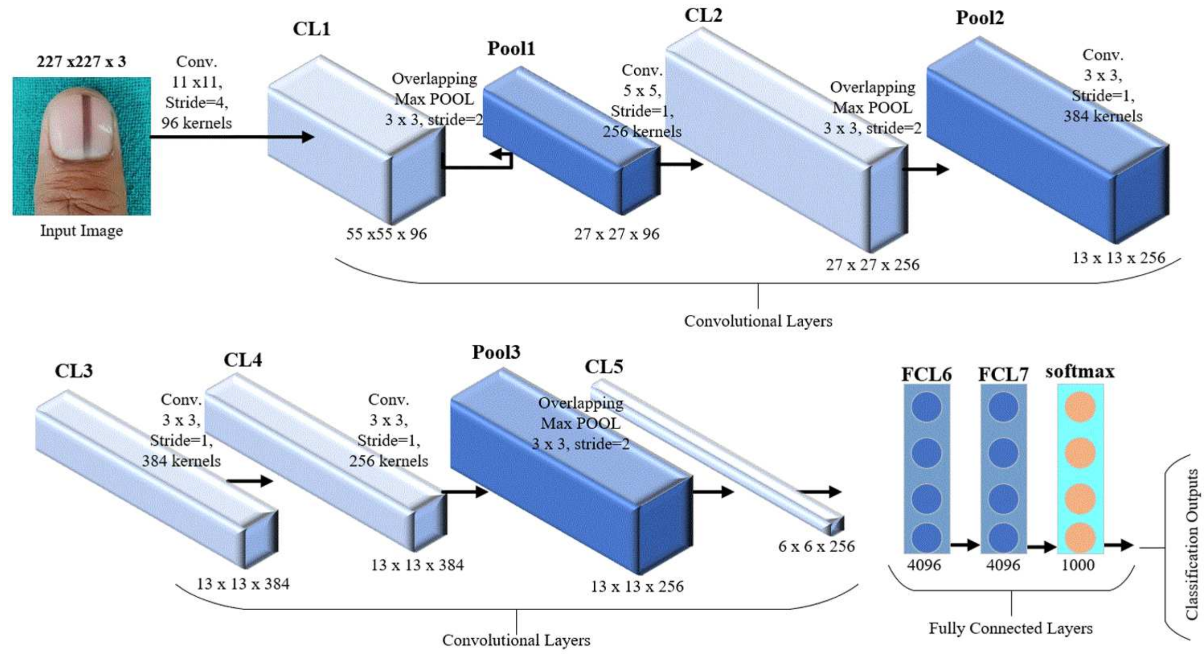


Figure 4. AlexNet architecture

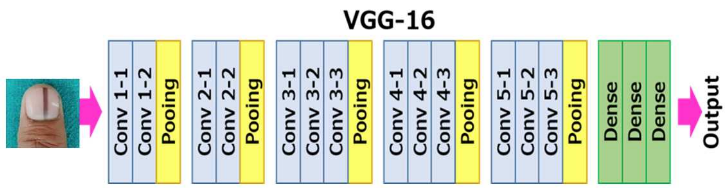


Figure 5. Vgg16 architecture

3.2.3. *GoogleNet.* In this study, the GoogleNet is presented based on the work of Szegedy et al. [22], who was the winner of ILSVRC in 2014 [27]. The GoogleNet has seven million parameters and contains nine inception modules, four CLs, four max-pooling layers, three average pooling layers, five FLCs and three SoftMax layers for the main auxiliary classifiers in the network [10]. Figure 6 shows an architecture of GoogleNet.

3.2.4. *ResNet50.* The network architecture of the Residual Network (ResNet) is shown in Figure 7. ResNet50 is a 50 layers deep CNN and it is already trained on more than a million images [27]. ResNet was successfully applied in biomedical image classification field for transfer learning [20].

3.2.5. *DenseNet201.* DenseNet is an abbreviation of the Dense CNN, this network needs a smaller number of parameters than a CNN, as it does not learn redundant feature maps [24]. Figure 8 shows the architecture of DenseNet201 model. DenseNet is the better model for image classification.

In this study, the number of layers and the size of input layer for each above mentioned models are summarized in Table 1.

Different parameters used for the training CNN models are explained in Table 2.

The CNN training is extremely computationally intensive. Therefore, all the experiments are done using a computer with Intel Core-i7, 2.2 GHz processor, 16 GB RAM, display system NAVIDIA GeForce GTX 1060 and Microsoft Windows 10 Enterprise, 64-bit operating system. All this information is summarized in Table 3. The training and testing operations are performed on MATLAB 2019b with transfer learning toolbox. Figure 9 shows the system architecture overview. The nail images are taken by a camera, and

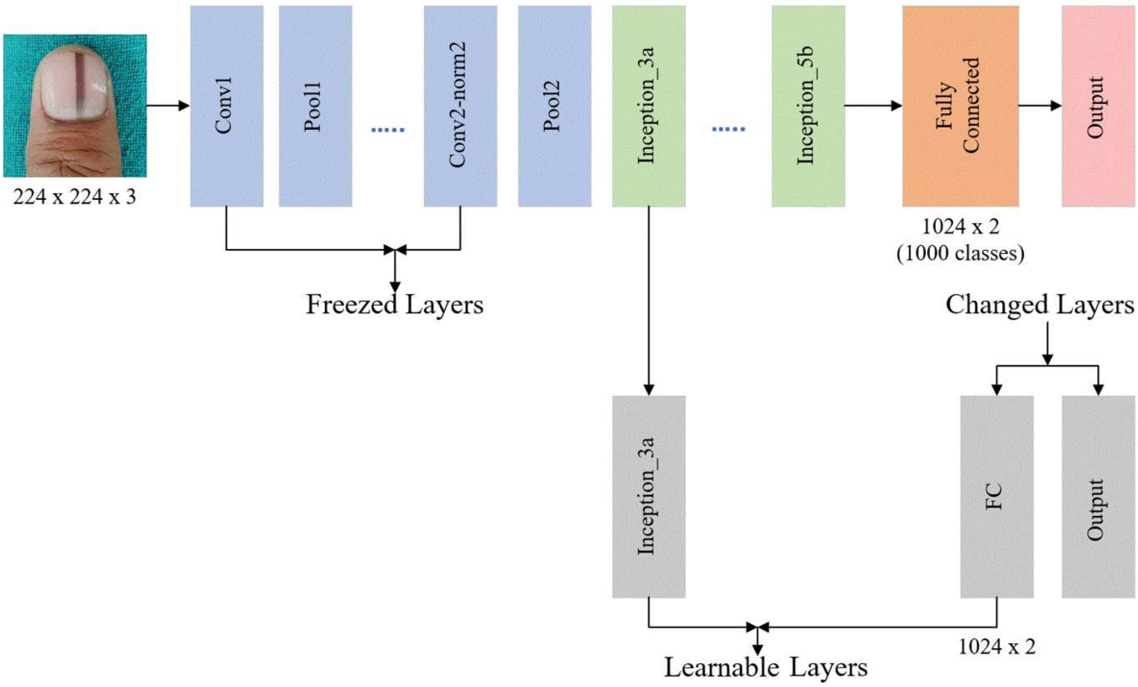


FIGURE 6. GoogleNet architecture

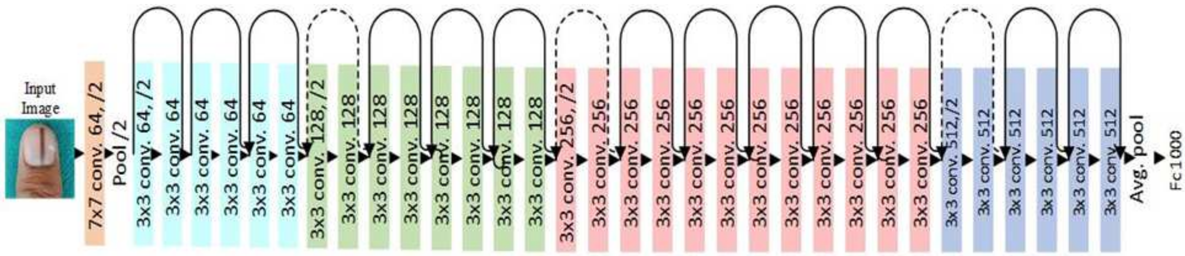


FIGURE 7. ResNet50 architecture

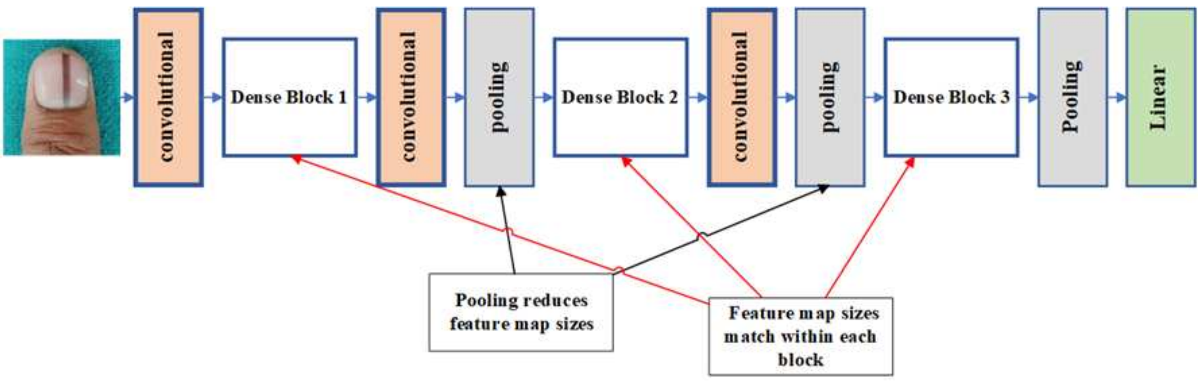


FIGURE 8. DenseNet201 architecture

TABLE 1. No. of layers and size of input layer for each model

Network	Input layer size	No. of layers
AlexNet	227×227	25
Vgg16	224×224	41
GoogleNet	224×224	144
ResNet50	224×224	177
DenseNet201	224×224	709

TABLE 2. Training parameters

Software	Network	Learning network	Mini batch size	Train: Test image percentage
MATLAB software	AlexNet	1.00E-04	10	60% : 40%
	Vgg16		10	
	GoogleNet		10	
	ResNet50		32	
	DenseNet201		32	

TABLE 3. Machine specification

Hardware and software	Characteristics
Processor	Intel Core^{TM}i7, 2.2 GHz
OS type	Microsoft Windows 10 Enterprise, 64 Bit
Display system	NAVIDIA GeForce GTX 1060
RAM	16 GB

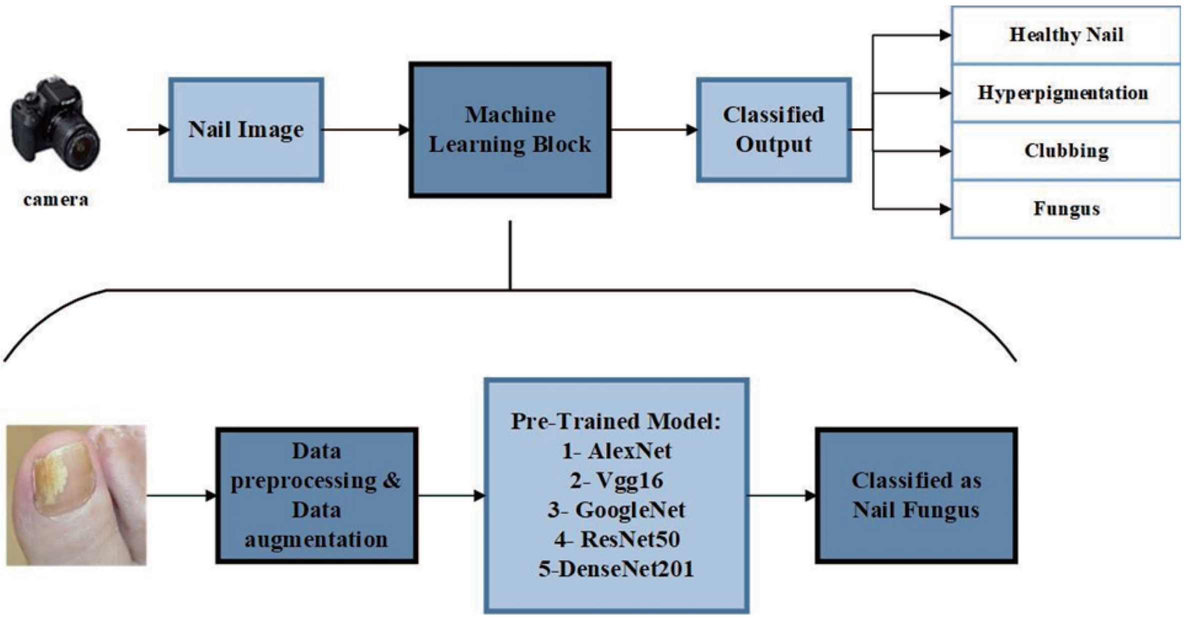


FIGURE 9. Overview of system architecture

then these images are processed through one of the TL models to detect and classify the type of nail diseases. Due to the limited images in nail diseases dataset and deep learning needs a huge dataset for training, data augmentation technique is used to increase the number of images for training. In data augmentation, there are many transformations to increase the images in dataset such as flipping, image rotation, image cropping, modification of image colors and random erasing.

3.3. **Performance evaluation.** The performance of the proposed methods is evaluated to compare the different used pre-trained models by calculating the different metrics [28]. Five metrics are calculated for comparison purpose. The first one is the sensitivity (recall), which refers to how many examples of the positive classes were labeled correctly; this can be calculated as follows:

$$\text{Sensitivity (Recall)} = \text{TP}/(\text{TP} + \text{FN}) \tag{1}$$

where the TP is referring to the true positive, which are the number of instances that are positive and are correctly identified, and FN refers to the false negative, which are the number of positive cases that are not classified correctly.

Specificity corresponds to the conditional probability of true negatives given a secondary class, which means that it approximates the probability of the negative label being true; it is represented by

$$\text{Specificity} = \text{TN}/(\text{TN} + \text{FP}) \tag{2}$$

where TN is the number of true negatives or negative cases that are negative and classified as negative, and FP is the number of false positives, defined by the negative instances that are incorrectly classified as positive cases. In general, sensitivity and specificity evaluate the effectiveness of the algorithm on a single class, positive and negative respectively.

Commonly, the accuracy is the most used metric to evaluate the classification performance [29]. In the evaluation stage, the accuracy was calculated every 20 iterations. This metric calculates the percentage of samples that are correctly classified, and it can be represented by

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{TN} + \text{FP} + \text{FN}) \tag{3}$$

On the other hand, the precision is defined as the number of true positives divided by the number of true positives plus the number of false positives, and it is expressed by

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}) \tag{4}$$

This measure is about correctness, i.e., it evaluates the predictive power of the algorithm. Precision is how "precise" the model is out of those predicted positive and how many of them are actually positive.

The final metric is the F-score, which determines the harmonic mean precision and recall, and it is defined

$$\text{F-score} = 2 \times (\text{Precision} \times \text{Recall})/(\text{Precision} + \text{Recall}) \tag{5}$$

It focuses on the analysis of positive class. A high value of this metric indicates that the model performs better on the positive class.

4. **Collection of Data.** The collection of data for any system is the most important part for system training to get a good result. In the deep learning, the algorithms need a strong dataset for the training of the models. The better training for the model, the more accuracy will be obtained in the testing.

In the field of nail diseases detection, there is no open-source dataset available. Due to this big problem, the data has been collected from many websites for our classification classes and the images are chosen with good quality and proper colors. Table 4 below shows the used nail classes and the number of images in each class. Figure 2 shows some of the nail images from the new collected dataset.

TABLE 4. The created dataset for nail diseases

Class	**No. of images**
Healthy nail	92
Nail hyperpigmentation	73
Nail clubbing	60
Nail fungus	55
Total	280

5. **Main Results.** In this comparison study, five Transfer Learning (TL) models were trained to classify four classes of human nail diseases images (healthy nail, nail hyperpigmentation, nail clubbing and nail fungus). The main objective of this research was to compare five of the TL models by calculating important parameters, through which we distinguish the efficiency of the system. These parameters are accuracy, precision, sensitivity (recall), specificity and F_score. The five models were AlexNet, Vgg16, GoogleNet, ResNet50 and DenseNet201. Table 5 below shows the results. For all five TL models trained in this research, DenseNet201 and ResNet50 exceed the remaining three models in all measured parameters. The accuracy of DenseNet201 and ResNet50 are the same, 96.39%. This is followed by GoogleNet with 93.98%, AlexNet with 92.5%. Vgg16 backs down to the last of the list in terms of all measured parameters, where the accuracy was 87.5%.

Table 5. Performance parameters (%) for every TL model

Parameters (%)	**Transfer learning model**				
	AlexNet	Vgg16	GoogleNet	ResNet50	DenseNet201
Accuracy	92.5	87.5	93.98	96.39	96.39
Sensitivity (Recall)	85	67.5	83.61	87.79	90.44
Specificity	95	88	95.87	97.65	97.47
Precision	87.46	74.62	86.8	88.9	91.12
F-score	84.68	73.89	84.52	88.11	90.63

DenseNet201 has the highest measure of sensitivity (Recall) with 90.44% followed by ResNet50 with 87.79%, AlexNet with 85% and GoogleNet with 83.61%. Here AlexNet surpassed on GoogleNet in this parameter. Finally, Vgg16 sensitivity was 67.5%. In the same way, in the order of specificity, F-score and precision, DenseNet201 topped the first place in these measures with 97.47%, 90.63% and 91.12% respectively. ResNet50 is in the second place with 97.65%, 88.11% and 88.9% for specificity, F-score and precision respectively. GoogleNet and AlexNet have approximately the same measures in specificity and F-score, GoogleNet with 95.87% and 84.52% for specificity and F-score respectively, while AlexNet 95% and 84.68%. In terms of precision, AlexNet surpassed on GoogleNet with 87.46% for AlexNet and 86.8% for GoogleNet. Finally, Vgg16 took the last place with 88%, 73.89% and 74.62% for specificity, F-score and precision respectively.

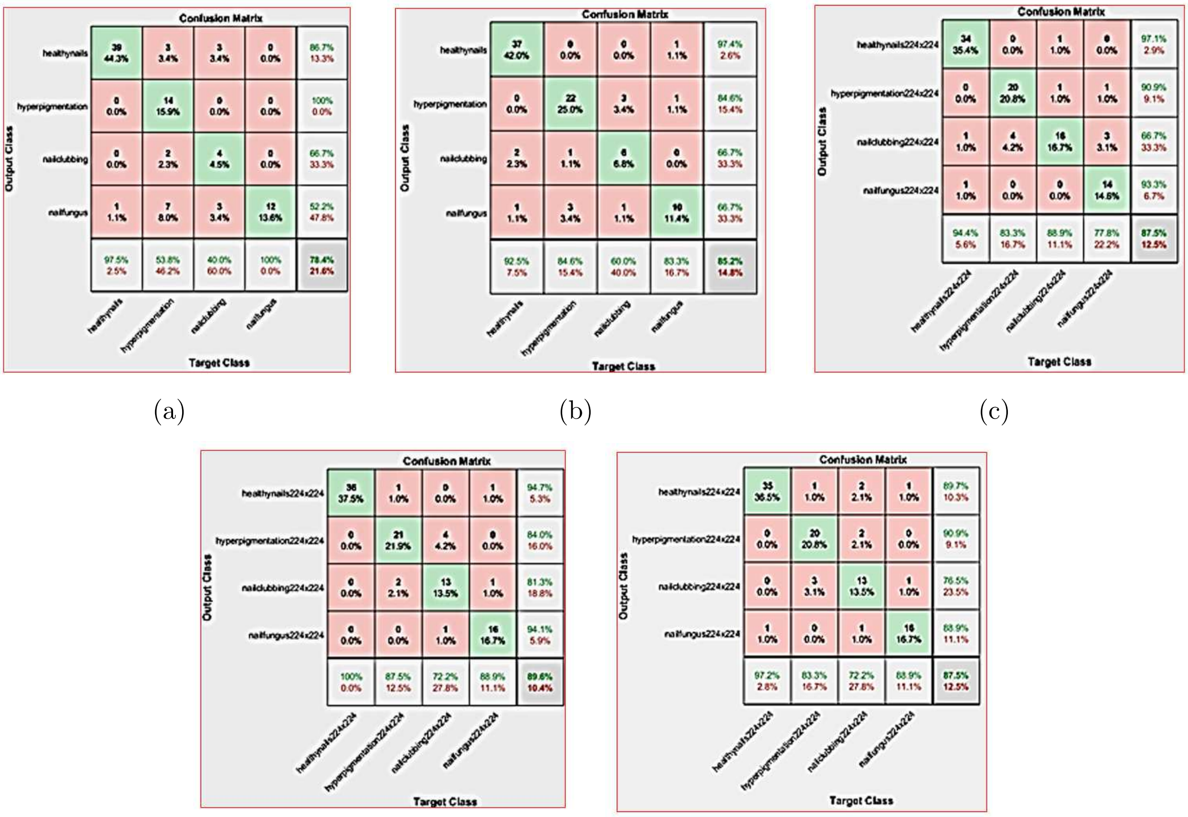
The last thing that must be talking about is time. Time is an important thing for system performance. The time of training and validation was calculated to see which system has the lowest training and validation time. AlexNet has time 13 secs and it was the lowest time, which means AlexNet was the faster model in training and validation. ResNet50 and DenseNet201 followed AlexNet with 15 secs and 26 secs respectively. GoogleNet and Vgg16 were the slowest models with 45 secs and 57 secs respectively. Table 6 summarized a comparison between these work and other similar researches in nail diseases classification. This work made classification for 4 classes of nail diseases and got more accuracy results in diseases detection from the other two researches as shown in Table 6.

Figure 10 shows the confusion matrices for the different five TL models that are used to classify four human nail classes. ReNet50 and DenseNet201 have the best validation values for all four classes of nail diseases images. Figure 11 shows some of the obtained classification images for the four used classes.

TL has the capabilities to classify any type of images. For this work, the used dataset is portioned into four classes (healthy nail, nail hyperpigmentation, nail clubbing and nail fungus) which have 92, 73, 60 and 55 images respectively. The dataset was divided into 60%-40% (training-testing). Five state-of-the-art TL models, namely AlexNet, Vgg16, GoogleNet, ResNet50 and DenseNet201 were used to train nail images. All of these

Table 6. Comparison with other recent similar papers

Author	Classes	TL or CNN model	No. of images	Accuracy	Precision
Naveen et al. [28], 2020	2 classes (unaffected and Leukonychia)	Vgg16	210	76%	74.30%
Yani et al. [12], 2019	2 classes (healthy nails and Terry's nails)	TensorFlow inception V3	215	94.39%	98%
This work	4 classes (healthy, hyperpigmentation, clubbing and fungus)	AlexNet	280	92.50%	87.46%
		Vgg16		87.50%	74.62%
		GoogleNet		93.98%	86.8%
		ResNet50		96.39%	88.9%
		DenseNet201		96.39%	91.12%



(a) (b) (c) (d) (e)

Figure 10. Confusion matrix for (a) AlexNet, (b) Vgg16, (c) GoogleNet, (d) ResNet50 and (e) DenseNet201

models were evaluated by various measures: accuracy, sensitivity (recall), specificity, F-score and precision. Based on Table 6 and Figure 10, which show general results and confusion matrices respectively, DenseNet201 achieved the better result than the other models. On the other hand, in terms of time, AlexNet took the first place in speed.

6. **Conclusion.** In this research five pre-trained TL models have been used to classify four nail diseases classes, and achieved 96.39% and it is a good accuracy from DenseNet201 model. Due to the unavailability of an existing dataset with perfect images of human nail diseases for training, the work gained more complexity, but it is imperative that there is scope for extension in the future. Our work may include application in an early detection of some of the human nail diseases which can get the required medical attention on time.

(a) (b) (c) (d)

Figure 11. Some of the classified images: (a) Healthy nail, (b) hyperpigmentation, (c) nail clubbing and (d) nail fungus

For future work, we aimed to create a dataset for nail diseases and test it by using pre-trained DenseNet201 model. Also, one can conduct a comparison study between nail based on deep learning and nail detection based on spiking neural network [30-33].

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