DIAGNOSING DISEASES FROM FINGERNAIL IMAGES

Zuhal CAN[1*], Sahin Isik[2]

[1] Eskişehir Osmangazi University, Faculty of Engineering and Architecture, Department of Computer Engineering, Eskişehir, Turkey, ORCID No : http://orcid.org/0000-0002-6801-1334

[2] Eskişehir Osmangazi University, Faculty of Engineering and Architecture, Department of Computer Engineering, Eskişehir, Turkey, ORCID No : http://orcid.org/0000-0003-1768-7104

Keywords

EfficientNet, Deep learning, Prediction web application

Abstract

In the medical domain, the human nail has the potential to give insight into a broad range of dermatological nail disorders. There are several approaches to early diagnosis of particular nail disease with shape and texture analysis through image processing stages, including capturing, processing, feature extraction, and classification steps. Through the use of image processing and deep learning techniques, this study investigates how the appearance of a person's fingers and nails can assist in the diagnosis of a variety of diseases. These diseases include Darier's disease, Muehrcke's lines, alopecia areata, beau's lines, bluish nails, and clubbing. We used a publicly available dataset that had a total of 656 samples and 17 distinct classes. For the purposes of training, validating, and testing our model, we partitioned the dataset into three folds according to a standard rule known as the 0.7:0.2:0.1. We evaluated the performance of the EfficientNet-B2 model utilizing Noisy-Student weights and a batch size and epoch count of 32 and 1,000, respectively. The algorithm detects fingernail illnesses with a 72% accuracy and 91% AUC score for test samples. This study's empirical data provides a fresh knowledge that the EfficientNet-B2 model can identify label of various types of nail diseases.

TIRNAK GÖRÜNTÜLERİNDEN HASTALIK TEŞHİSİ

Anahtar Kelimeler

EfficientNet, Derin öğrenme, Tahmin ağ uygulaması

Öz

Tıp alanında, insan tırnağı, çok çeşitli dermatolojik tırnak bozuklukları hakkında fikir verme potansiyeline sahiptir. Yakalama, işleme, öznitelik çıkarma ve sınıflandırma adımlarını içeren görüntü işleme aşamaları ile şekil ve doku analizi aracılığıyla belirli tırnak hastalığının erken teşhisine yönelik birkaç yaklaşım vardır. Bu çalışmada, görüntü işleme ve derin öğrenme tekniklerini kullanarak, bir kişinin parmaklarının ve tırnaklarının görünümünün çeşitli hastalıkların teşhisine nasıl yardımcı olabileceğini araştırılmaktadır. Bu hastalıklar arasında Darier hastalığı, Muehrcke çizgileri, alopesi areata, beau çizgileri, mavimsi tırnaklar ve çomaklaşma yer alır. Toplamda 656 örnek ve 17 farklı sınıfa sahip halka açık bir veri kümesi kullanılmıştır. Modelimizi eğitmek, doğrulamak ve test etmek amacıyla, veri seti 0.7:0.2:0.1 olarak bilinen standart bir kurala göre üç bölüme ayrılmıştır. EfficientNet-B2 modelinin performansını, Noisy-Student ağırlıkları ve sırasıyla 32 ve 1.000 parti boyutu ve dönem sayısı kullanarak değerlendirilmiştir. Algoritma, test numuneleri için %72 doğruluk ve %91 AUC puanı ile tırnak hastalıklarını tespit etmektedir. Bu çalışmanın deneysel verileri, EfficientNet-B2 modelinin çeşitli tırnak hastalıklarının etiketlerini tanımlayabildiğine dair taze bir bilgi sağlamaktadır.

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1. Introduction

People may have conditions that can be underlying symptoms of severe diseases. Early detection of these diseases is vital to increase the chance of overcoming them. However, people often neglect to go to the hospital or seek professional medical help; it is common for people to just search for their conditions from online

* Corresponding Author; e-mail : zcan@ogu.edu.tr

sources. Without a professional opinion, symptoms that were not caught in the disease's early stages can grow to further stages.

One of the symptoms of many diseases is the appearance of fingernails. This study aims to accurately diagnose diseases from the appearance of one's fingernails through fingernails images' disease identification process. For this purpose, a disease diagnosing system is developed using a deep learning model to classify fingernail diseases, including alopecia areata, beau's lines, bluish nail, clubbing, darier disease, eczema, half and half nails (Lindsay's nails), koilonychias, leukonychia, muehrcke's lines, onycholysis, pale nail, red lunula, splinter hemorrhage, terry's nail, white nails, and yellow nails. This system consists of a web application based on a deep learning model developed by the EfficientNet-B2 model. Patients who are worried about the health of their fingernails can take a picture of their fingernails and upload it to the system for a quick diagnosis, with a success rate of 72%.

This study presents a diagnosing disease system based on fingernail images. In section 2, we include a literature review on the subject. In Section 3, we propose the disease diagnosing model on fingernail images. Our findings are presented in Section 4, and we include a discussion and conclude the paper in Section 5. We hypothesize that this system will raise awareness of the disease symptoms based on fingernail appearances and contribute to the existing knowledge on deep learning in the related medical fields.

2. Literature Review

Deep learning-based approaches are increasingly prominent techniques in various artificial intelligence research areas to automate diagnostic processes and decision-making (Watson, Cooper, Palacio, Moran, & Poshyvanyk, 2022)(Yang, Hu, & Li, 2020)(Gustisyaf & Sinaga, 2021).

In recent years, there has been an increase in deep learning applications in biomedical research, especially in medical diagnostics. The medical diagnostics research focuses on developing healthcare through medical imaging technology and medical data analysis (Meijering, 2020)(Mansour, Althobaiti, & Ashour, 2021)(Iqbal, Sharif, Yasmin, Raza, & Aftab, 2022). Various kinds of biomedical images such as ultrasound (Cammarasana, Nicolardi, & Patanè, 2022), X-rays (Sharma et al., 2022), MRI (Lundervold & Lundervold, 2019), or other clinical images (Esteva et al., 2017) (Mansour et al., 2021) can be the domain of deep learning-based medical diagnostics. Medical diagnostic research includes detecting and analyzing the related disease to recognize the disease's existence, type, and level (Kovalev, Liauchuk, Voynov, & Tuzikov, 2021)(Thanikachalam et al., 2022).

EfficientNet (Tan & Le, 2019) is a novel convolutional neural network architecture for analyzing images and is preferred as a prediction model in various disease diagnostic research for humans (Venugopal, Joseph, Das, & Nath, 2022)(Nayak, Padhy, Mallick, Zymbler, & Kumar, 2022)(Wang, Liu, Xie, Yang, & Zhou, 2021)(Ravi, Acharya, & Alazab, 2022)(Zhu et al., 2022)(Marques, Ferreras, & de la Torre-Diez, 2022) and plants (Hanh, Van Manh, & Nguyen, 2022)(Farman et al., 2022)(Atila, Uçar, Akyol, & Uçar, 2021)(Li, Liu, Li, & Liu, 2022). EfficientNet's popularity among deep learning researchers is due to its high classification and prediction performances. EfficientNet's performance is compared with other deep learning models in various studies, and, EfficientNet is found to perform better than others (Nayak et al., 2022)(Zhu et al., 2022)(Marques et al., 2022)(Atila et al., 2021)(Li et al., 2022).

For automating the diagnostic process, several software applications are developed (Gómez-de-Mariscal et al., 2021)(Azman & Kairuddin, 2022)(Tsutsumi et al., 2021). Our study focuses on developing a web-based application for diagnosing 17 fingernail diseases based on EfficientNet deep learning model and public dataset images.

There are several studies in the literature for fingernail disease classification. Banu and Devi compared the performance of various classifiers, such as SVM and KNN, based on an image dataset of eight types of abnormalities (Thahira Banu & Devi, 2021). Indi and Patil analyzed the color, shape, and features of fingernails and applied SVM, KNN, and ANN classifiers for predicting diseases (Indi & Patil, 2019). Izadi et al. studied the existence of fungus through various convolutional neural network models including InceptionResNetV2, MobilenetV2, Xception, ResNet-101, NasNetMobile, DenseNet (Izadi, Morovati, Ranjbaran, & Homayounmajd, 2021). Mehra et al. classified and diagnose two fingernail diseases based on several deep learning models, including VGG-16, VGG-19, ResNet50, and DenseNet121 (Mehra, D'Costa, D'Mello, George, & Kalbande, 2021). Maniyan and Shivakumar extracted 13 features from nail color, shape, and texture of nails and classified fingernail diseases based on the KNN classifier (Maniyan & Shivakumar, 2018). Yani et al. studied the existence of Terry's Nail using Inception-V3 architecture (Yani & others, 2019). In another study (Abdulhadi, Al-Dujaili, Humaidi, & Fadhel, 2021), it was examined four forms of nail illnesses, including healthy nails, nail hyperpigmentation, nail clubbing, and nail fungus. The obtained dataset's samples were categorized using five pretrained deep Convolutional Neural Network (CNN) models (AlexNet, Vgg16, GoogleNet, ResNet50 and DenseNet201). The highest recognition rate was obtained with ResNet50 as 96.40%. In a traditional approach (Safira, Irawan, & Setianingsih, 2019), it was aimed to identify abnormalities in Terry's nail. For this purpose, textural features were analyzed using grey level co-occurrence matrix (GLCM) and the KNN classifier. The best accuracy result was 70.93% with K=1.

None of these studies performed EfficientNet for fingernail disease classification and diagnostics. To the best of our knowledge, this is the first web-based deep-learning application developed for fingernail disease diagnostics based on the EfficientNet model.

3. Method

Research and publication ethics are followed in this study.

3.1. Dataset

The dataset comprises 655 fingernail photos of 17 diseases collected from Kaggle datasets (Kaggle, 2022), as shown in Table 1.

Table 1

Total Amount of Images in Each Disease Class

Disease Class	Number of Images
Aloperia areata	47
Beau's lines	42
Bluish nail	50
Clubbing	40
Darier_s disease	47
Eczema	45
Lindsay_s nails	38
Koilonychia	38
Leukonychia	31
Muehrck-e's lines	33
Onycholycis	50
Pale nail	35
Red lunula	15
Splinter hemmorrage	62
Terry's nail	36
White nail	19
Yellow nails	27

3.2. System Design

The fingernail diagnosing system comprises a front-end and a back-end development with a deep learning model as depicted in Figure 1. The front-end is a web application that is built using web development technologies, including Python, HTML5, CSS3, JavaScript, and ReactJS. The front-end web application allows images to be uploaded into the server and be evaluated based on the deep learning model.

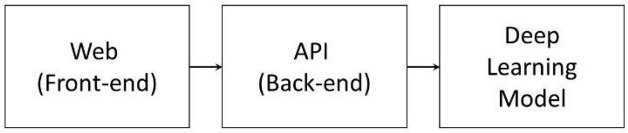


Figure 1. The Nail Diseases Prediction web application system

Web-based nail-disease recognition system is written in python code using Flask web framework. Flask uses a templates folder for reading and rendering HTML files; and a static folder for reaching CSS and js files. In the python code, the prediction model is uploaded to the system by load_model function as given below:

model = load_model(MODEL_PATH, compile = False)

model.predict(image) predicts the class of the given image. In our system, uploaded images are stored in the uploads directory, and the prediction results are posted to the web browser.

The back-end runs on NodeJS as a server. Back-end development involves importing required libraries into the Python environment, including Tensorflow, Keras, NumPy, pyplot, OpenCV, and sklearn libraries.

Data need to be split into separate sets by a portion of 0.7:0.2:0.1 for training, testing and validation using splitfolders.ratio function from splitfolders module. All the images are resized to be the same size. The image size is 224x224x3 px. Then dataset is checked, and images are labeled by classes.

3.3. Deep Learning Method

We have applied the transfer learning methodology using EfficientN2-B2 as the base model and two different CNN2d layers as fully connected layers with the goal of improvıng the performance. The first CNN2d includes 128 filters, and the second consists of 64 filters. Besides, we used Adam optimizer for updating weights in a fast, robust and flexible way. As an improvement, we have used Noisy Student Weights in the case of compiling the model. Also, we have integrated GlobalAveragePooling2D and Dropout(0.1) layers for modification.

Overfitting occurs when a model learns the attributes of the training set and predicts based on generalization. To tackle the problem of overfitting, we have applied data augmentation techniques to better generalization. The augmentation technique modifies and expands old data by flipping, rotating, or zooming horizontally or vertically. The horizontal/vertical rotate, rotation (10 degree), shear_range (0.1), zoom_range (0.1) and normalized with ImageNet mean and standard deviation values for color images (224x224x3 px). The deep learning model is developed on colab.research.google.com and saved as a file with hdf5 extension.

3.4. Performance Metrics

Model accuracy, precision, recall, F-score are calculated based on the prediction amount of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FT) as shown in (1), (2), (3) and (4), respectively. The area under the Receiver Operator Characteristic (ROC) curve is defined as AUC (Area Under Curve). The AUC measures the test's ability to classify all nail diseases correctly (Fangyu & Hua, 2018).

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \quad (1)$$

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \quad (2)$$

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \quad (3)$$

$$F - Score = 2 * \frac{\mathrm{Precision} * \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \quad (4)$$

4. Results

Model results are given in Table 2 in summary and in Figure 2 in more detail. Table 2 presents the scores of our model in 17 different classes. Our accuracy is 0.72 % for these classes. Figure 2 lists individual scores for each classes. Error rates for each class on test set is demonstrated in Figure 3.

Table 2

Performance Results of the Deep Learning Model

Model	Accuracy	AUC	Precision	Recall	F-Score
Noisy-Student Weights-Adam	0.72	0.91	0.71	0.73	0.72

	precision	recall	f1-score
Darier_s disease	0.73	0.73	0.73
Muehrck-e_s lines	0.86	0.86	0.86
aloperia areata	0.48	1.00	0.65
beau_s lines	0.45	0.56	0.50
bluish nail	0.90	0.90	0.90
clubbing	0.70	0.88	0.78
eczema	1.00	0.80	0.89
Lindsay_s nails	0.75	0.67	0.71
koilonychia	0.67	0.44	0.53
leukonychia	0.80	0.57	0.67
onycholycis	0.69	0.90	0.78
pale nail	0.50	0.38	0.43
red lunula	1.00	0.50	0.67
splinter hemmorrage	0.82	0.69	0.75
terry_s nail	0.57	0.50	0.53
white nail	0.67	0.40	0.50
yellow nails	0.80	0.57	0.67

Figure 2. Performances of each Disease Class

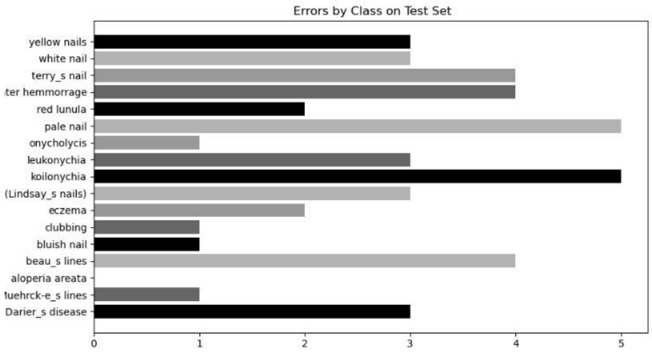


Figure 3. Errors of Classes on the Test Set

The confusion matrix is the visualization of the model's performance that demonstrates whether the system is confusing classes. The significant amount of zeros in the confusion matrix, as shown in Figure 4, proves that the given model distinguished among classes with good accuracy.

The Nail Diseases Prediction web application interprets the predictions and prints the result to the screen for web users. The application asks users to upload an image and evaluate the uploaded image based on the developed model. For model evaluation, the saved model is loaded by load_model() function of tensorflow.keras.models module, and then, the predict() function is called to make predictions about uploaded images. This web application allows continuous image uploads. Users can reset the system to view the clean page with the reset button. The application is run on localhost, and some predictions of the application are shown in Figure 5.

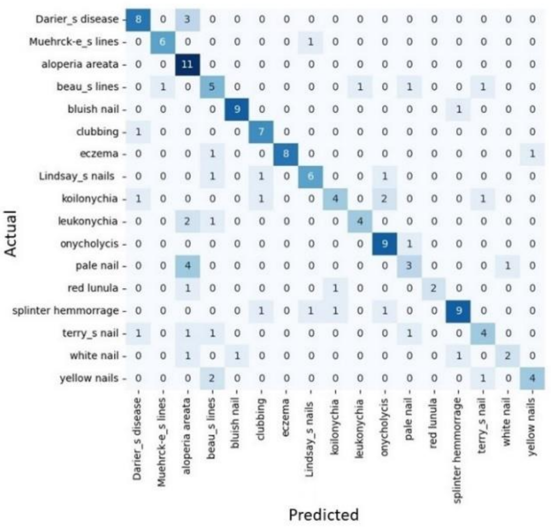
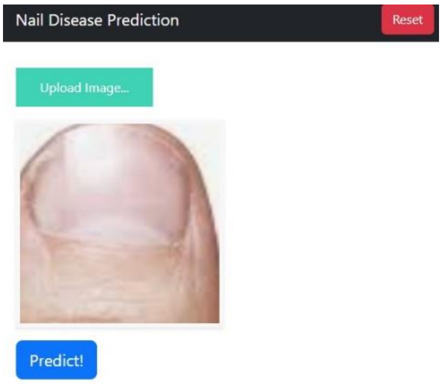
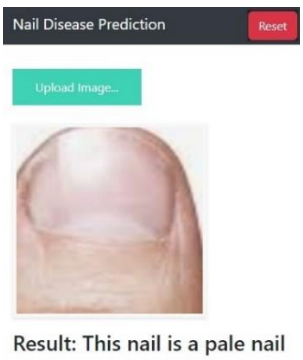


Figure 4. Confusion Matrix of the Prediction Results on Each Classification

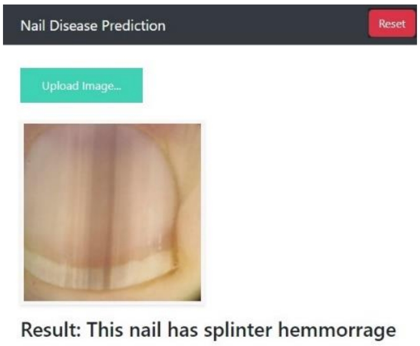
a. Web page view before upload.



b. Web page view before prediction.



c. Web page view after prediction.



d. Web page view after prediction of another disease.

Figure 5. Screenshots of the Nail Diseases Prediction Web Application

5. Discussion and Conclusion

In this study, we have developed a web-based application for diagnosing 17 fingernail diseases based on the EfficientNet-B2 model. This study aims to enlighten patients with an accurate prediction of their conditions based on fingernail images through deep learning solutions and a web-based fingernail disease identification system. This system diagnoses nail diseases with high accuracy (72%) with availability for everyone from the ease of their homes. Compared to the studies in the literature, this is the first web-based deep-learning application developed for fingernail disease diagnostics based on the EfficientNet model. Even though our detection score appears low, we have utilized many different classes. In contrast to the literature, which only considers binary classification or a small number of classifications, our real-time system performs on 17 distinct categories.

This system can be improved by including more pictures into the dataset with images of healthy and ill nails. Fingernail diseases may correlate with the presence of certain disorders. Further studies can address the relationship between nail diseases and skin cancer. We believe that this study will help save lives by catching diseases in their early stages.

Conflict of Interest

No conflict of interest was declared by the authors.

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References

Abdulhadi, J., Al-Dujaili, A., Humaidi, A. J., & Fadhel, M. A.-R. (2021). *Human Nail Dıseases Classification based on transfer learning*.

Atila, Ü., Uçar, M., Akyol, K., & Uçar, E. (2021). Plant leaf disease classification using EfficientNet deep learning model. *Ecological Informatics*, *61*, 101182.

Azman, K. A., & Kairuddin, W. N. H. W. (2022). Disease Classification by Human Fingernail Colour Image Processing. *Evolution in Electrical and Electronic Engineering*, *3*(1), 180–190.

Cammarasana, S., Nicolardi, P., & Patanè, G. (2022). Real-time denoising of ultrasound images based on deep learning. *Medical & Biological Engineering & Computing*, 1–16.

Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, *542*(7639), 115–118.

Fangyu, L. I., & Hua, H. E. (2018). Assessing the accuracy of diagnostic tests. *Shanghai Archives of Psychiatry*, *30*(3), 207.

Farman, H., Ahmad, J., Jan, B., Shahzad, Y., Abdullah, M., & Ullah, A. (2022). EfficientNet-Based Robust Recognition of Peach Plant Diseases in Field Images. *CMC-COMPUTERS MATERIALS & CONTINUA*, *71*(1), 2073–2089.

Gómez-de-Mariscal, E., Garcia-López-de-Haro, C., Ouyang, W., Donati, L., Lundberg, E., Unser, M., … Sage, D. (2021). DeepImageJ: A user-friendly environment to run deep learning models in ImageJ. *Nature Methods*, *18*(10), 1192–1195.

Gustisyaf, A. I., & Sinaga, A. (2021). Implementation of Convolutional Neural Network to Classification Gender based on Fingerprint. *International Journal of Modern Education & Computer Science*, *13*(4).

Hanh, B. T., Van Manh, H., & Nguyen, N.-V. (2022). Enhancing the performance of transferred efficientnet models in leaf image-based plant disease classification. *Journal of Plant Diseases and Protection*, *129*(3), 623–634.

Indi, T. S., & Patil, D. D. (2019). Nail Feature Analysis and Classification Techniques for Disease Detection. *Int. J. Comput. Sci. Eng*, *7*(5), 1376–1383.

Iqbal, A., Sharif, M., Yasmin, M., Raza, M., & Aftab, S. (2022). Generative adversarial networks and its applications in the biomedical image segmentation: a comprehensive survey. *International Journal of Multimedia Information Retrieval*, 1–36.

Izadi, V., Morovati, M., Ranjbaran, G., & Homayounmajd, S. (2021). An Empirical Study of Nail Fungus Classification Using Deep and Traditional Machine Learning Methods. *Journal of Bioengineering Research*, *3*(3), 16–23.

Kaggle. (2022). Nail Dataset. Retrieved from https://www.kaggle.com/datasets/reubenindustrustech/nail-dataset-new

Kovalev, V. A., Liauchuk, V. A., Voynov, D. M., & Tuzikov, A. V. (2021). Biomedical Image Recognition in Pulmonology and Oncology with the Use of Deep Learning. *Pattern Recognition and Image Analysis*, *31*(1), 144–162.

Li, B., Liu, B., Li, S., & Liu, H. (2022). An Improved EfficientNet for Rice Germ Integrity Classification and Recognition. *Agriculture*, *12*(6), 863.

Lundervold, A. S., & Lundervold, A. (2019). An overview of deep learning in medical imaging focusing on MRI. *Zeitschrift Für Medizinische Physik*, *29*(2), 102–127.

Maniyan, P., & Shivakumar, B. L. (2018). Early Disease Detection Through Nail Image Processing Based On Ensemble Of KNN Classifier And Image Features. *IOSR Journal of Computer Engineering (IOSR-JCE)*, *20*(3).

Mansour, R. F., Althobaiti, M. M., & Ashour, A. A. (2021). Internet of things and synergic deep learning based biomedical tongue color image analysis for disease diagnosis and classification. *IEEE Access*, *9*, 94769–94779.

Marques, G., Ferreras, A., & de la Torre-Diez, I. (2022). An ensemble-based approach for automated medical diagnosis of malaria using EfficientNet. *Multimedia Tools and Applications*, 1–18.

Mehra, M., D'Costa, S., D'Mello, R., George, J., & Kalbande, D. R. (2021). Leveraging Deep Learning for Nail Disease Diagnostic. *2021 4th Biennial International Conference on Nascent Technologies in Engineering (ICNTE)*, 1–5.

Meijering, E. (2020). A bird's-eye view of deep learning in bioimage analysis. *Computational and Structural Biotechnology Journal*, *18*, 2312–2325.

Nayak, D. R., Padhy, N., Mallick, P. K., Zymbler, M., & Kumar, S. (2022). Brain Tumor Classification Using Dense Efficient-Net. *Axioms*, *11*(1), 34.

Ravi, V., Acharya, V., & Alazab, M. (2022). A multichannel EfficientNet deep learning-based stacking ensemble approach for lung disease detection using chest X-ray images. *Cluster Computing*, 1–23.

Safira, L., Irawan, B., & Setianingsih, C. (2019). K-Nearest Neighbour Classification and Feature Extraction GLCM for Identification of Terry's Nail. *2019 IEEE International Conference on Industry 4.0, Artificial Intelligence, and Communications Technology (IAICT)*, 98–104.

Sharma, S., Gupta, S., Gupta, D., Rashid, J., Juneja, S., Kim, J., & Elarabawy, M. M. (2022). Performance evaluation of the deep learning based convolutional neural network approach for the recognition of chest X-ray images. *Frontiers in Oncology*, *12*.

Tan, M., & Le, Q. V. (2019). *EfficientNet: improving accuracy and efficiency through AutoML and model scaling. Google AI Blog*.

Thahira Banu, V., & Devi, M. R. (2021). Hybrid Classifier to Classify The Finger Nail Abnormalities. *Information Technology In Industry*, *9*(1), 549–555.

Thanikachalam, V., Shanthi, S., Kalirajan, K., Abdel-Khalek, S., Omri, M., & Ladhar, L. M. (2022). Intelligent Deep Learning Based Disease Diagnosis Using Biomedical Tongue Images. *CMC-Computers Materials & Continua*, *70*(3), 5667–5681.

Tsutsumi, K., Goshtasbi, K., Risbud, A., Khosravi, P., Pang, J. C., Lin, H. W., … Abouzari, M. (2021). A web-based deep learning model for automated diagnosis of otoscopic images. *Otology & Neurotology*, *42*(9), e1382--e1388.

Venugopal, V., Joseph, J., Das, M. V., & Nath, M. K. (2022). An EfficientNet-based modified sigmoid transform for enhancing dermatological macro-images of melanoma and nevi skin lesions. *Computer Methods and Programs in Biomedicine*, 106935.

Wang, J., Liu, Q., Xie, H., Yang, Z., & Zhou, H. (2021). Boosted efficientnet: Detection of lymph node metastases in breast cancer using convolutional neural networks. *Cancers*, *13*(4), 661.

Watson, C., Cooper, N., Palacio, D. N., Moran, K., & Poshyvanyk, D. (2022). A Systematic Literature Review on the Use of Deep Learning in Software Engineering Research. *ACM Transactions on Software Engineering and Methodology (TOSEM)*, *31*(2), 1–58.

Yang, X., Hu, Q., & Li, S. (2020). Recognition and classification of damaged fingerprint based on deep learning fuzzy theory. *Journal of Intelligent & Fuzzy Systems*, *38*(4), 3529–3537.

Yani, M., & others. (2019). Application of transfer learning using convolutional neural network method for early detection of terry's nail. *Journal of Physics: Conference Series*, *1201*(1), 12052.

Zhu, S., Lu, B., Wang, C., Wu, M., Zheng, B., Jiang, Q., … Yang, W. (2022). Screening of common retinal diseases using six-category models based on EfficientNet. *Frontiers in Medicine*, 130.