Jurnal Teknik Informatika (JUTIF)
P-ISSN: 2723-3863
E-ISSN: 2723-3871

Vol. 7, No. 2, April 2026, Page. 926-936
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5347

A Smart System for Non-Invasive Early Detection of Diabetes through Deep Learning-Based Nail Image Analysis and Expert Systems

Muhammad Zulfikri*[1], Wirajaya Kusuma[2], Naufal A. Furqan[3]

[1,3]Information Technology, Bumigora University, Indonesia
[2]Software Engineering, Bumigora University, Indonesia

Email: [1]mzulfikri@universitasbumigora.ac.id

Received : Sep 28, 2025; Revised : Nov 5, 2025; Accepted : Nov 28, 2025; Published : Apr 15, 2026

Abstract

Public health in Indonesia faces significant challenges in the early detection of diseases, particularly in areas with limited medical services. Diabetes Mellitus can lead to serious complications, but its detection is often hindered by limited access to invasive and expensive diagnostic methods. This study aims to develop a non-invasive early detection system through nail image analysis using a deep learning method based on EfficientNet-B7 and a rule-based expert system. The system classifies nail images into five categories: Healthy, Beaus lines, Onycholysis, Onychomycosis, and Paronychia. The evaluation results show an accuracy of 97.11% on the test set, demonstrating excellent performance in detecting nail conditions associated with diabetes. The application of the expert system using Forward Chaining and Certainty Factor provides in-depth medical explanations for the model's predictions, making this system a potential solution for diabetes screening that is fast, affordable, and accessible across various healthcare facilities.

Keywords: *Deep learning, Diabetes mellitus, Early detection, Expert system, Nail images.*

1. INTRODUCTION

Public health in Indonesia faces challenges in early disease detection, especially in areas with limited medical services. Nail conditions can serve as indicators of systemic disorders such as Diabetes Mellitus (DM), which often remain undetected until serious complications arise. Studies have shown that nail changes reflect microcirculatory disturbances in DM patients [1], [2], [3]. DM, projected to affect over 40 million people in Indonesia by 2045 [4], can lead to complications such as nephropathy and cardiovascular diseases [5]. Nail abnormalities, such as onychomycosis, paronychia, and onycholysis, are frequently found in diabetic patients and are correlated with peripheral circulation disorders [6], [7]. Conventional diagnostic methods, such as blood tests, are invasive, costly, and not widely available in areas with limited medical infrastructure [8], [9]. Technology-based non-invasive approaches, such as nail image analysis, could offer an effective solution for early diabetes screening with low costs and broader access.

Research on diabetes detection through nail image analysis has shown potential as a non-invasive screening method; however, many previous studies still used conventional neural networks without leveraging the more efficient deep learning techniques. For instance, research with simple neural networks achieved 84.6% accuracy without an expert system [9], [10], [11]. Recent studies using Capsule-CNN reached an accuracy of 99.25% [12], but methods like laser spectroscopy and capillaroscopy require specialized equipment that is less practical [13], [14]. The EfficientNet-B7 architecture chosen for this study excels in medical image classification with high accuracy on nail capillary abnormalities (97.3%) [15], [16], [17]. EfficientNet is more efficient than classic CNNs because it uses compound scaling to increase image depth and resolution proportionally [18], [19], [20].

Jurnal Teknik Informatika (JUTIF) Vol. 7, No. 2, April 2026, Page. 926-936
P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5347

Expert systems based on forward chaining and Certainty Factor enhance the interpretability of results and handle uncertainty [21], [22], [23]. This research also builds on previous experience in image classification systems, such as vehicle detection and face recognition using SVM and Viola-Jones [24], [25].

This study aims to develop a non-invasive early detection system for diabetes through nail image analysis using deep learning and an expert system. The system classifies nail images based on three main abnormalities related to diabetes and provides recommendations through a rule-based system using forward chaining and certainty factor. EfficientNet-B7 is used to identify nail features, with data validated through Confusion Matrix, ROC-AUC, and F1-score. Unlike previous studies that only used conventional neural networks or methods requiring specialized equipment, this research integrates deep learning and expert systems for severity estimation and medical recommendations. This study is expected to be a fast, inexpensive, and easy-to-apply screening method, with potential for development as an AI-based self-screening application.

2. METHOD

This study aims to develop an intelligent early detection system for Diabetes Mellitus (DM) in a non-invasive manner through nail image analysis using deep learning methods and a rule-based expert system. The system combines visual image analysis with rule-based reasoning to provide a more accurate and reliable estimation of risk and severity levels. A workflow of the research is presented in Figure 1.

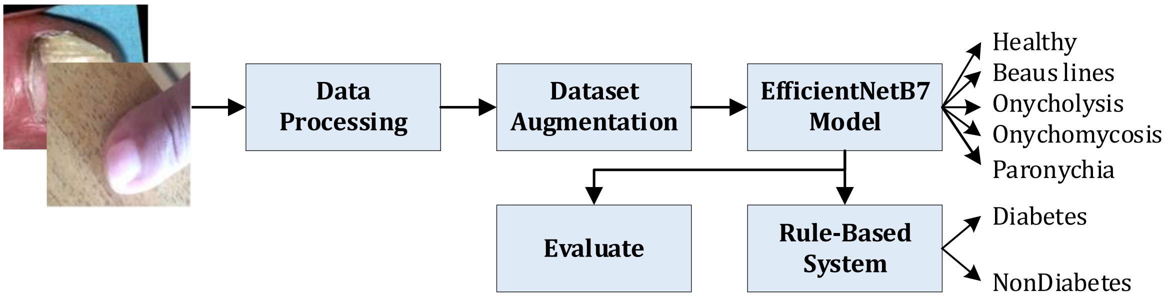


Figure 1. Workflow of the EfficientNetB7 Model for Nail Disease Classification

The dataset used in this study is crucial for diagnosing and researching diabetes. This dataset consists of 6.100 images sourced from publicly accessible platforms, Roboflow (https://universe.roboflow.com/) and Kaggle (https://www.kaggle.com/), and is divided into five classes: healthy with 1.300 images, beaus_lines with 1.250 images, onycholysis with 950 images, onychomycosis with 1.300 images, and paronychia with 1.300 images. These images are instrumental in linking healthy nails with diseased nails or those associated with diabetes. Figure 2 shows a sample from each class in the Nail Image Dataset.

Figure 2. Nail disease images used in the dataset.

Vol. 7, No. 2, April 2026, Page. 926-936
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5347

2.1. Data Preprocessing

After the dataset is collected, the preprocessing stage is carried out to prepare the data for model training. One of the key steps in preprocessing is resizing the image resolution, where the images are transformed into a 600x600 pixel size, in accordance with the input requirements for EfficientNetB7, which optimizes the model's performance with consistent image sizes [26], [27]. After that, pixel normalization is performed by scaling the pixel values from [0, 255] to [0, 1] to enhance training efficiency and accelerate model convergence. These two steps ensure that the processed image data are of optimal quality and can be effectively used in deep learning model training.

2.2. Dataset Augmentation

Image augmentation is an important method in Deep Learning (DL) to prevent overfitting and improve the model's generalization ability [28]. In this study, after preprocessing, the data is divided into three parts: training, validation, and testing, with a split ratio of 75:15:15, as shown in **Table 1**. For the training data, augmentation is applied to increase data diversity without the need to collect new data, while also ensuring a balance in the number of images in each class, with a target of 950 images per class. The augmentation techniques used include rescale (scaling pixel values to the range [0, 1]), image rotation up to 20°, horizontal and vertical image shifting, zooming up to 20%, and horizontal flipping. This process allows the model to detect objects with different image variations, improving accuracy and enriching the training dataset.

Table 1. Data Division for Nail Image Dataset

Disease	Training Images	Validation Images	Testing Images
Healthy	909	195	196
Onychomycosis	909	195	196
Onycholysis	665	142	143
Paronychia	909	195	196
Beaus Lines	875	187	188

2.3. EfficientNet B7 Model

EfficientNet is a family of convolutional neural networks developed by Google to balance depth, width, and resolution through compound scaling. The models range from B0 to B7, with EfficientNetB7 being the largest and most accurate model, though it requires more resources [29], [30]. EfficientNetB7, pre-trained on ImageNet, was chosen in this study due to its computational efficiency and good accuracy with fewer parameters compared to other models. The model development process involves Transfer Learning, where the feature extraction layers are frozen and only the top layers are fine-tuned for the nail disease dataset, as well as the Addition of Classification Layers to enhance training stability and prevent overfitting.

Model training uses the balanced and augmented dataset, with a focus on fine-tuning the top layers. The training process is conducted in three stages: Optimization and Loss Function using Adamax and categorical_crossentropy, Regularization and Callbacks with Dropout and BatchNormalization, and Training for 30 epochs. The model is trained to adapt to the more specific dataset, improving the classification accuracy of nail diseases. The model structure developed is presented in Table 2, which details the model architecture, including the added feature extraction and classification layers.

P-ISSN: 2723-3863
https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5347

Table 2. The Developed Model Structure

Layer (type)	Output Shape	Parameter
efficientnetb7 (Functional)	(None, 2560)	64,097,687
batch_normalization	(None, 2560)	10,24
Dropout	(None, 2560)	0
Dense	(None, 256)	655,616
dropout_1	(None, 256)	0
batch_normalization_1	(None, 256)	1,024
dense_1	(None, 128)	32,896
dropout_2	(None, 128)	0
dense_2	(None, 5)	645
Total params		**64,798,108**
Trainable params		**63,941,801**
Non-trainable params		**856,307**

2.4. Rule-Based System

After the model is trained, a Rule-Based System is used to provide further explanations about the prediction results. This system combines Forward Chaining and Certainty Factor (CF) to provide medical context. Forward Chaining begins with the model's prediction result as a fact and searches for related medical rules. CF indicates the level of certainty of the prediction, which is calculated using the following formula:

$$CF = \frac{Confidence}{Maximum\ Confidence} \qquad (1)$$

Where Confidence is the model's confidence level in the predicted class, and Maximum Confidence is the highest confidence level that can be achieved for that class based on the trained data.

The application of CF in the expert system involves several rules, such as Forward Chaining to link the predicted class with the associated medical conditions. For example, if the prediction is Clubbing, the system will associate it with circulatory disorders or diabetes. Based on the predicted class, CF is assigned according to the known relationship with medical conditions, with the application rules presented in **Table 3**. The final output of this system is the predicted class along with the CF value, which indicates the level of certainty of the relationship between the nail condition and the related medical disease, such as diabetes. If the prediction is Healthy, the status is NonDiabetes with a low CF, while for other classes, the status indicates diabetes with the corresponding condition description

Table 3. Predicted Class and Medical Description

Predicted Class	Status	CF	Medical Description
Onychomycosis	Diabetes	0.95	Fungal infection on the nails, very common in diabetes patients.
Onycholysis	Diabetes	0.8	Nails detaching from the nail bed, often associated with diabetic neuropathy.
Beaus Lines	Diabetes	0.55	Beau's lines may indicate metabolic disorders including diabetes.
Paronychia	Diabetes	0.45	Infection around the nail, common in diabetes patients.
Healthy	NonDiabetes	0.1	Healthy nails, no signs of diabetes.

Jurnal Teknik Informatika (JUTIF) Vol. 7, No. 2, April 2026, Page. 926-936
P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5347

2.5. Evaluate

Testing is conducted to measure the model's ability to classify previously unseen images using test data. The evaluation includes a confusion matrix for accuracy, ROC and AUC to differentiate classes, and the F1-score to measure the balance between precision and recall. Accuracy, sensitivity, and specificity are also calculated to provide an overall performance overview of the model in classification, detecting positive classes, and detecting negative classes.

3. RESULT

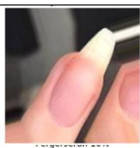
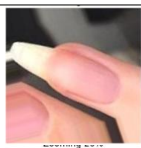
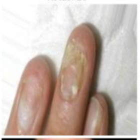
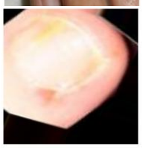
The experiment was conducted on a computer system with the following specifications: Intel Core i5 processor, 16 GB RAM, 64-bit Windows operating system running at 1.80 GHz, with an A100 Colab GPU. Python was chosen as the programming language for executing the experiment, and several important libraries used include pandas, NumPy, matplotlib, keras, tensorflow, and other relevant libraries.

3.1. Data Preprocessing and Augmentation

In the preprocessing stage, the images are resized to 600x600 pixels to meet the input requirements of EfficientNet-B7, ensuring consistent image sizes. Next, pixel normalization is performed by scaling the pixel values from [0, 255] to [0, 1], which enhances training efficiency and accelerates model convergence.

Image augmentation is applied to increase data diversity and reduce overfitting, ensuring a balanced number of images in each class. The techniques used include rotation, shifting, zooming, and horizontal flipping, which enrich the image variations and help the model recognize patterns more effectively. Table 4 shows the augmented images for each class.

Table 4. Augmented Images per Class

Class	Original Images	Rotation 20°	Shift 10%	Zooming 20%	Flipping Horizontal	Brightness 5%
Healthy						
Onycholysis						
Onychomycosis						
Paronychia						
Beaus Lines						

Vol. 7, No. 2, April 2026, Page. 926-936
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5347

3.1.1. Model Training and Fine-Tuning

The model training was carried out using the Adamax optimizer and categorical_crossentropy as the loss function. During Epoch 1, the training accuracy was 22% with a loss of 4.9171, while the validation accuracy was 30.67% with a loss of 4.3437. By Epoch 30, the training accuracy increased to 97.44%, and the loss reduced to 2.0313. The validation accuracy at Epoch 30 was 96.76%, with a loss of 2.0130, as shown in Figure 3. While the training and validation accuracies showed significant improvement, there was a slight drop in the test set accuracy. This suggests that the model may not have been fully optimized for classifying certain difficult classes, such as Beaus lines and Onychomycosis.

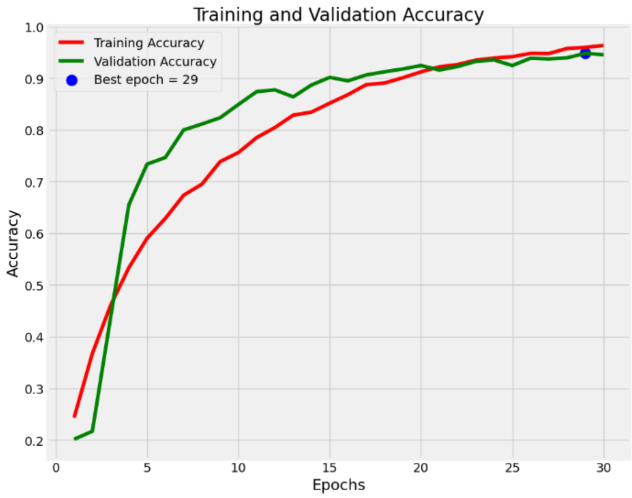


Figure 3. Training and Validation Accuracy over 30 Epochs

To address this, fine-tuning was performed on the model using a lower learning rate (1e-5) to improve stability and reduce the risk of overfitting. The model that was trained during the initial phase was then further fine-tuned for 20 epochs using the re-trained dataset. Fine-tuning adjustments were made to the top layers of the model, with a lower learning rate and callbacks to monitor performance during training. During fine-tuning Epoch 1, the training accuracy was 83.40% with a loss of 4.8712, while the validation accuracy was 93.33% with a validation loss of 4.4501. By Epoch 20, the training accuracy increased to 92.47%, with the loss decreasing to 2.9525. The validation accuracy at Epoch 20 was 94.44%, with a validation loss of 2.7685, as shown in Figure 4.

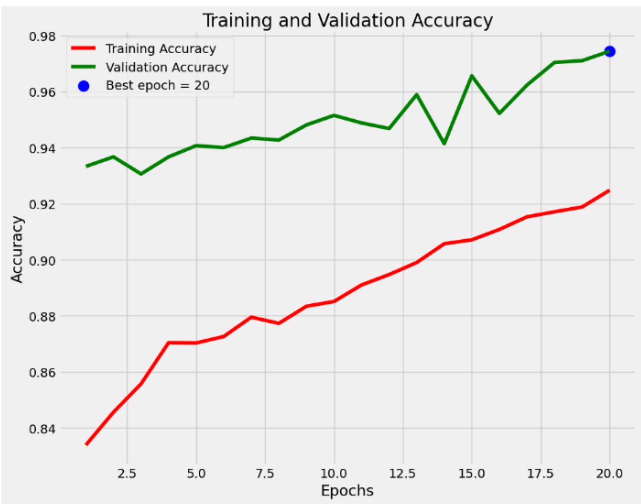


Figure 4. Training and Validation Accuracy during Fine-Tuning

P-ISSN: 2723-3863
E-ISSN: 2723-3871
Vol. 7, No. 2, April 2026, Page. 926-936
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5347

3.1.2. Rule-Based System

After evaluating the model, the prediction results were further processed using a **Rule-Based System** with **Forward Chaining** and **Certainty Factor (CF)**. This expert system links the predicted class to related medical conditions using predefined rules. The results from testing five different classes are presented in Figure 5. This system provides the predicted class alongside the **CF** value, indicating the level of certainty in the relationship between the nail condition and the related medical disease, such as diabetes.

(a) (b) (c)

(d) (e)

Figure 5. Prediction Results of Nail Images for Each Class, Including CF to Show Certainty Level (a) Healthy, (b) Onychomycosis, (c) Onycholysis, (d) Beaus Lines, (e) Paronychia

In conclusion, this study successfully developed a non-invasive early detection system for Diabetes Mellitus using nail image analysis with EfficientNet-B7 and a rule-based expert system based on forward chaining and CF. The model demonstrated high accuracy in classifying nail diseases related to diabetes. Augmenting the dataset with techniques such as rotation, zooming, and horizontal flipping helped increase image variability, allowing the model to recognize patterns from different nail conditions. However, challenges remain in classifying more complex conditions like Beaus lines and Onychomycosis, indicating the need for further data collection and improved augmentation techniques for these classes.

Jurnal Teknik Informatika (JUTIF) Vol. 7, No. 2, April 2026, Page. 926-936
P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5347

3.2. Evaluation

Once the fine-tuning process was completed, the model was tested on a separate test set to evaluate its ability to classify unseen images. The classification report for the test set is shown in Table 4, where the model achieved a high accuracy of 97% on the test set. Paronychia had the highest accuracy (1.00), while Beaus Lines achieved an F1-score of 0.99 (shown in Table 5). The Confusion Matrix was used to evaluate the distribution of classification errors, showing that the model was able to detect most classes with high accuracy, but with some errors in harder-to-classify classes such as Beaus lines and Onychomycosis. Overall, the model shows solid performance in classifying nail disease images, which is presented in Figure 6.

Table 5. Classification Report on Test Set

Class	Precision	Recall	F1-Score	Support
Beaus Lines	0.98	1.00	0.99	300
Healthy	0.98	0.97	0.97	300
Onycholysis	0.94	0.94	0.94	285
Onychomycosis	0.95	0.95	0.95	301
Paronychia	1.00	1.00	1.00	300
Accuracy			**0.97**	**1486**

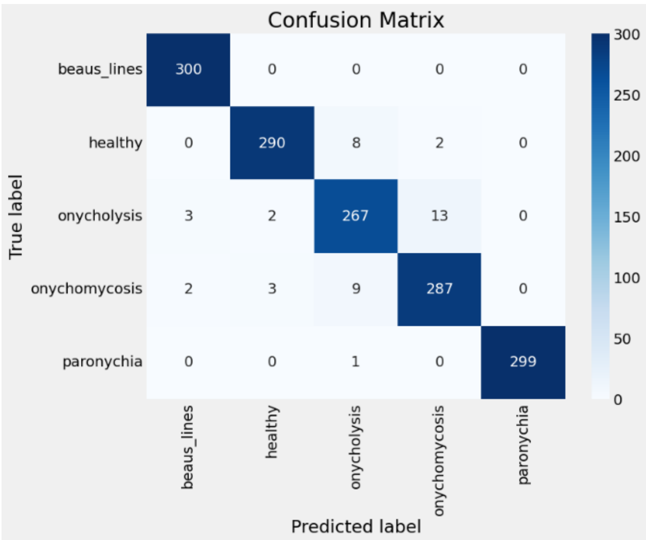


Figure 6. Confusion Matrix from the Test Set during Fine-Tuning

4. DISCUSSIONS

This study shows that the use of EfficientNet-B7 and a Forward Chaining-based expert system can improve disease detection accuracy through nail image analysis. Compared to previous studies, this research provides an update in early diabetes detection with a more affordable and accessible non-invasive approach (shown in Table 6).

Overall, this study demonstrates that with the use of advanced machine learning methods such as Hybrid Capsule CNN, EfficientNet-B7, and transfer learning, we can achieve very high detection accuracy in diagnosing nail disorders and diabetes. By combining more complex algorithms and technologies like expert systems, model accuracy and efficiency can be enhanced, providing better solutions for non-invasive disease detection. These findings contribute to the development of faster,

Vol. 7, No. 2, April 2026, Page. 926-936
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5347

more affordable, and accessible early detection systems across various healthcare facilities. The key contribution of this research is the use of a Forward Chaining and Certainty Factor-based expert system, which provides deeper medical explanations and rule-based recommendations, as well as the use of EfficientNet-B7, which is highly efficient in medical image classification. This makes the system not only accurate but also more widely accessible, addressing the urgent need for early diabetes detection in areas with limited medical facilities.

Table 6. Comparison with previous research

Paper Title	Year	Dataset	Algorithm
Fingernail Diagnostics: Advancing type II diabetes detection using machine learning algorithms and laser spectroscopy [14]	2024	80 nail samples, 40 diabetic and 40 control	PCA + 7 classifiers (ensemble learning) = 96%
Autonomous detection of nail disorders using a hybrid capsule CNN: a novel deep learning approach for early diagnosis[12]	2024	Nail Disease Detection dataset	Hybrid Capsule CNN = 99,40
Abnormality detection in nailfold capillary images using deep learning with EfficientNet and cascade transfer learning [16]	2025	225 NFC images (Normal & Abnormal)	EfficientNet-B0 + cascade transfer learning = 99%
A Smart System for Non-Invasive Early Detection of Diabetes through Deep Learning-Based Nail Image Analysis and Expert Systems	2025	6,100 nail images from Roboflow & Kaggle, 5 classes	EfficientNet-B7 + Expert System (Forward Chaining & Certainty Factor)=97,11%

5. CONCLUSION

This study successfully developed a non-invasive early detection system for Diabetes Mellitus through nail image analysis using deep learning with EfficientNet-B7 and a rule-based expert system based on forward chaining and Certainty Factor (CF). The model achieved an accuracy of 97.11% on the test set, proving its effectiveness in classifying nail conditions related to diabetes. However, Beaus lines and Onychomycosis remain challenging classes to classify. This system has great potential to be used as a fast, affordable, and easy-to-implement diabetes screening method, especially in areas with limited access to medical facilities.

To improve the system's performance, it is recommended to expand the dataset with more images from the difficult-to-classify classes, as well as using advanced data augmentation techniques such as GAN to generate more diverse images. The development of AI-based applications for self-administered diabetes screening could broaden access to early detection, particularly in underserved areas. Future research could also consider integrating additional medical data, such as patient health history, to enhance the model's accuracy.

ACKNOWLEDGEMENT

Thank you to the Directorate General of Higher Education, Research and Technology of the Republic of Indonesia for funding this research activity through the 2025 Beginner Lecturer Research scheme.

REFERENCES

[1] U. Sujianto and I. Riniatsih, "Peningkatan Pengetahuan dan Kesadaran Masyarakat Terhadap Deteksi Dini Penyakit Deabetes Melitus dan Hipertensi," *J. Pengabdi. Perawat*, vol. 1, no. 1, pp. 1–6, 2022, doi: 10.32584/jpp.v1i1.1513.

[2] L. C. Ratri *et al.*, "The Potential of Nail Glycation Examination for Detecting Diabetes Mellitus:

Vol. 7, No. 2, April 2026, Page. 926-936
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5347

A Systematic Review and Meta-Analysis," *Res. J. Pharm. Technol.*, vol. 17, no. 9, pp. 4528–4534, 2024, doi: 10.52711/0974-360X.2024.00700.

[3] S. Widaty *et al.*, "Clinical and microbiological characteristics of onychomycosis in a tertiary hospital: a cross-sectional study," *Med. J. Indones.*, vol. 33, no. 1, pp. 17–23, 2024, doi: 10.13181/mji.oa.247201.

[4] M. Wahidin *et al.*, "Projection of diabetes morbidity and mortality till 2045 in Indonesia based on risk factors and NCD prevention and control programs," *Sci. Rep.*, vol. 14, no. 1, 2024, doi: 10.1038/s41598-024-54563-2.

[5] I. Leila, Huned Materwala, and Juma Al Kaabi 2, "Association of Risk Factors with Type 2 Diabetes : A Systematic Review," *Comput. Struct. Biotechnol. J.*, vol. 7, no. 4, pp. 1759–1785, 2021, doi: 10.23887/jst-undiksha.v14i2.100794.

[6] P. Vidyasagar and B. P. Kumar, "Toe nail changes in diabetes mellitus," *IP Indian J. Clin. Exp. Dermatology*, vol. 7, no. 1, pp. 40–46, 2021, doi: 10.18231/j.ijced.2021.008.

[7] M. Satasia and A. H. Sutaria, "Nail Whispers Revealing Dermatological and Systemic Secrets: An Analysis of Nail Disorders Associated With Diverse Dermatological and Systemic Conditions," *Cureus*, vol. 15, no. 9, pp. 1–20, Sep. 2023, doi: 10.7759/cureus.45007.

[8] D. Lazaro-Pacheco, P. F. Taday, and P. M. Paldánius, "Exploring in-vivo infrared spectroscopy for nail-based diabetes screening," *Biomed. Opt. Express*, vol. 15, no. 3, pp. 1926–1942, Mar. 2024, doi: 10.1364/BOE.520102.

[9] I. Kurniastuti, A. Andini, and M. R. Dwisapta, "Implementation of Neural Network for Classification of Diabetes Mellitus through Finger Nail Image," in *Procedia Computer Science*, Elsevier, Jan. 2024, pp. 1625–1632. doi: 10.1016/J.PROCS.2024.03.166.

[10] C. Unigarro, J. Hernandez, and H. Florez, "Artificial Neural Networks for Image Processing in Precision Agriculture: A Systematic Literature Review on Mango, Apple, Lemon, and Coffee Crops," *Informatics*, vol. 12, no. 2, 2025, doi: 10.3390/informatics12020046.

[11] C. Krupadanam, R. Narendran, and V. Thiruchelvam, "Comparing the accuracy of a convolutional neural network algorithm with K-nearest neighbors algorithm for the cardiac diagnosis," *AIP Conf. Proc.*, vol. 3161, no. 1, p. 20243, 2024, doi: 10.1063/5.0229269.

[12] G. Shandilya *et al.*, "Autonomous detection of nail disorders using a hybrid capsule CNN: a novel deep learning approach for early diagnosis," *BMC Med. Inform. Decis. Mak.*, vol. 24, no. 1, pp. 1–19, 2024, doi: 10.1186/s12911-024-02840-5.

[13] V. Gaurav, C. Grover, M. Tyagi, and S. Saurabh, "Artificial Intelligence in Diagnosis and Management of Nail Disorders: A Narrative Review," *Indian Dermatol. Online J.*, vol. 16, no. 1, pp. 40–49, Jan. 2025, doi: 10.4103/idoj.idoj_460_24.

[14] I. Rehan, K. Rehan, S. Sultana, and M. Ur Rehman, "Fingernail Diagnostics: Advancing type II diabetes detection using machine learning algorithms and laser spectroscopy," in *Microchemical Journal*, Elsevier, Jun. 2024, p. 110762. doi: 10.1016/J.MICROC.2024.110762.

[15] D. R. Raman, S. Nishanthi, and P. Babysha, "Diagnosis of Diabetic Retinopathy by using EfficientNet-B7 CNN Architecture in Deep Learning," in *2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS)*, 2023, pp. 430–435. doi: 10.1109/ICSCSS57650.2023.10169453.

[16] M. Ebadi Jalal, O. S. Emam, C. Castillo-Olea, B. García-Zapirain, and A. Elmaghraby, "Abnormality detection in nailfold capillary images using deep learning with EfficientNet and cascade transfer learning," *Sci. Rep.*, vol. 15, no. 1, p. 2068, 2025, doi: 10.1038/s41598-025-85277-8.

[17] Z. Huang, L. Su, J. Wu, and Y. Chen, "Rock Image Classification Based on EfficientNet and Triplet Attention Mechanism," *Appl. Sci.*, vol. 13, no. 5, 2023, doi: 10.3390/app13053180.

[18] L. Alzubaidi *et al.*, "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," *J. Big Data*, vol. 8, no. 1, 2021, doi: 10.1186/s40537-021-00444-8.

[19] D. Moch., Syahrir; I, Nyoman, Switrayana; I, Made, Angga, Wahyu, "Integrasi Bagging dan Stacking untuk Memperbaiki Kinerja Algoritma Klasifikasi C4.5 dan K-Nearest Neighbor (KNN)," *J. Sains dan Teknol.*, vol. 14, no. 2, pp. 218–228, 2025.

[20] Y. Segal, O. Hadar, and L. Lhotska, "Using EfficientNet-B7 (CNN), Variational Auto Encoder

Vol. 7, No. 2, April 2026, Page. 926-936
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5347

(VAE) and Siamese Twins' Networks to Evaluate Human Exercises as Super Objects in a TSSCI Images," *J. Pers. Med.*, vol. 13, no. 5, 2023, doi: 10.3390/jpm13050874.

[21] Z. E. Fitri, E. M. Ramadania, N. S. Wibowo, I. P. D. Lesmana, and A. M. N. Imron, "A Combination of Forward Chaining and Certainty Factor Methods for Early Detection of Fever : Dengue Hemorrhagic Fever, Malaria and Typhoid," *Sci. J. Informatics*, vol. 9, no. 1, pp. 23–31, 2022, doi: 10.15294/sji.v9i1.33007.

[22] D. A. P and L. Isyriyah, "Rancang Model Expert System pada Diagnosa Penyakit Diabetes Melitus dengan Metode Forward Chaining," *J. Teknol. dan Manaj. Inform.*, vol. 7, no. 1, pp. 51–61, 2021, doi: 10.26905/jtmi.v7i1.5930.

[23] B. Saputra, A. Utami, Edriyansyah, and Y. Irawan, "Expert System for Diagnosing Diseases in Toddlers Using the Certainty Factor Method," *J. Appl. Eng. Technol. Sci.*, vol. 4, no. 1, pp. 32–41, 2022, doi: 10.37385/jaets.v4i1.916.

[24] M. Zulfikri, W. Kusuma, S. Hadi, H. Husain, R. Hammad, and L. Z. A. Mardedi, "Speed Bump System Based on Vehicle Speed using Adaptive Background Subtraction with Haar Cascade Classifier," *Sistemasi*, vol. 13, no. 3, p. 1054, 2024, doi: 10.32520/stmsi.v13i3.3921.

[25] L. Z. A. Mardedi, M. Zulfikri, M. Syahrir, K. A. Latif, and Apriani, "Face Recognition for Personal Data Collection using Eigenface, Support Vector Machine, and Viola Jones Method," *Sistemasi*, vol. 14, no. 1, pp. 135–146, 2025, doi: https://doi.org/10.32520/stmsi.v14i1.

[26] M. Daga, D. Parikh, and S. P. Ramu, "DeepSeqCoco: A Robust Mobile Friendly Deep Learning Model for Detection of Diseases in Cocos Nucifera," in *IEEE Access*, 2025, pp. 89367–89385. doi: 10.1109/ACCESS.2025.3571800.

[27] U. Haziq *et al.*, "Improving lung cancer detection with enhanced convolutional sequential networks," *Sci. Rep.*, vol. 15, no. 1, p. 32099, 2025, doi: 10.1038/s41598-025-06653-y.

[28] C. Shorten and T. M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning," *J. Big Data*, vol. 6, no. 1, p. 60, 2019, doi: 10.1186/s40537-019-0197-0.

[29] Y. Pamungkas and D. S. Eljatin, "Hyperparameter Tuning of EfficientNet Method for Optimization of Malaria Detection System Based on Red Blood Cell Image," *J. Sisfokom (Sistem Inf. dan Komputer)*, vol. 13, no. 3, pp. 360–368, 2024, doi: 10.32736/sisfokom.v13i3.2257.

[30] Z. Can and Ş. Işık, "Diagnosing Diseases From Fingernail Images," *Eskişehir Osmangazi Üniversitesi Mühendislik ve Mimar. Fakültesi Derg.*, vol. 30, no. 3, pp. 464–470, 2022, doi: 10.31796/ogummf.1111749.