Bioinformatics-driven deep learning for nail disease diagnosis: a novel approach to improve healthcare outcomes

Rian Ardianto[1*], *Dede* Yusuf[2], *Raden Bagus Bambang* Sumantri[2], *Dina* Febrina[3], *Rosyid R.* Al-Hakim[4], and *Arif Setia Sandi* Ariyanto[4]

[1]Department of Informatics, Universitas Harapan Bangsa, 53144 Karangklesem Purwokerto Selatan, Indonesia
[2]Department of Informatics, Universitas Al-Irsyad Cilacap, 53223 Wanasari Sidanegara Cilacap Tengah, Indonesia
[3]Department of Pharmacy, Universitas Harapan Bangsa, 53182 Raden Patah Ledug Banyumas, Indonesia
[4]Department of Information System, Universitas Harapan Bangsa, 53144 Karangklesem Purwokerto Selatan, Indonesia

Abstract. In order to increase awareness of the importance of nail care in preventing disease and enhancing quality of life, this study investigates the use of convolutional neural networks, or CNNs. Onychomycosis and other nail disorders are quite prevalent worldwide and are associated with inadequate personal cleanliness. The study used a dataset of 655 nail photos that had been pre-processed to 224x224 pixel resolution and categorized into 17categories.The CNN model performed well in identifying illnesses like "Leukonychia," achieving an overall accuracy of 83%; however, it needs to be improved for underrepresented classifications like "Pale Nail." The study recommends data augmentation, model parameter optimization, and dataset expansion to improve accuracy. To confirm dependability in practical contexts, testing with clinical datasets is also advised. A user-friendly interface for wider accessibility is one of the future aims, which will allow for prompt and precise preliminary diagnosis. This study shows how CNN-based technologies can be used to quickly and easily identify nail disorders, improving access to treatment and preventing disease

1 Introduction

Personal hygiene is one of the fundamental aspects of personal health that is often overlooked, particularly in nail care. Unclean and poorly maintained nails can become a breeding ground for bacteria, viruses, and parasites, which can lead to various diseases [1]. Research shows that poor nail cleaning habits can increase the risk of skin infections, digestive disorders, and even respiratory illnesses. Individuals who rarely trim their nails or clean them properly tend to have long and dirty nails, providing an ideal environment for microorganisms to thrive [2]. Therefore, raising public awareness about the importance of

*Corresponding author: rianardianto@uhb.ac.id

nail care is a crucial step in preventing the spread of diseases and improving quality of life. Poor personal hygiene has become one of the leading causes of various dangerous diseases worldwide. Conditions such as gastrointestinal infections, skin diseases, and respiratory illnesses are often linked to poor hygiene practices [3]. One commonly neglected aspect of personal hygiene is nail care. Dirty and unkempt nails can serve as breeding grounds for bacteria and fungi, leading to serious infections like paronychia and onychomycosis. Nail infection cases are not only prevalent in developing countries but also occur in developed nations, indicating that nail hygiene is a global health issue that requires special attention [4].

Onychomycosis, a fungal nail infection, shows a significant prevalence according to results from six recent studies, which estimate an average prevalence of 5.5%. This condition is one of the most common skin diseases worldwide. For example, a questionnaire survey involving 10,000 people in the United Kingdom reported an onychomycosis prevalence of 2.71%. Recent mycological surveys in Finland and the United States also revealed relatively high prevalence rates, ranging from 7% to 10% [5]. In Indonesia, the focus on socioeconomic issues and other health-related diseases has led to limited awareness of onychomycosis, both among doctors and the general public. In 2017, onychomycosis accounted for 15% of all dermatophytosis cases, with only 25% of patients achieving recovery. Data from ten university hospitals in Indonesia during the 1997-1998 period showed an average onychomycosis incidence of 3.2% among all fungal skin diseases. Meanwhile, in Makassar, the prevalence was reported to be 3.6% of fungal skin diseases [6]. The large population living in areas with limited access to hygiene facilities contributes to the high number of nail disease cases. Data from the Ministry of Social Affairs in Indonesia indicates that nail infections such as paronychia and onychomycosis are common in various regions, particularly in rural areas [7]. This issue is exacerbated by the public's lack of awareness regarding the importance of nail hygiene and the scarcity of effective health education. As a result, many nail infections go untreated, leading to serious complications and negatively impacting the quality of life. The lack of concern for nail hygiene is often driven by social, economic, and cultural factors [8]. In many communities, nail care is not considered a priority, and information regarding the importance of nail hygiene is still very limited. Additionally, the lack of access to proper hygiene facilities, such as clean water and soap, poses a major challenge. Some cultures even have traditions that do not support proper nail hygiene, viewing it as insignificant. As a result, many individuals are unaware of the health risks associated with unkempt nails. More intensive health education and community outreach are essential to changing this behavior and promoting better hygiene practices [9]. Organizing campaigns on the importance of nail care, along with providing handwashing facilities and nail care tools in public spaces, can help reduce the incidence of infections caused by poor nail hygiene [10]. Additionally, involving community leaders and stakeholders in social activities and health education can accelerate behavioral change. With a comprehensive and sustainable approach, it is hoped that communities will become more aware of personal hygiene, including nail care, leading to better overall public health [11]. Early detection and accurate diagnosis of nail diseases, such as paronychia and onychomycosis, remain significant challenges in healthcare, both globally and in Indonesia. Nail diseases are often not diagnosed in the early stages due to symptoms that resemble other nail conditions, coupled with limited access to adequate medical facilities in many areas [12]. As a result, untreated nail infections can progress into more serious conditions, causing pain, discomfort, and even systemic complications. Therefore, innovative solutions are needed to improve the ability to detect and diagnose nail diseases quickly and accurately [13]. Deep learning, a branch of artificial intelligence (AI), has shown great potential in the medical field, particularly in image analysis and disease detection. By leveraging bioinformatics data, deep learning models can be trained to recognize specific patterns and characteristics of nail diseases through the analysis of medical images [14]. This technique involves collecting

images of both infected and healthy nails, which are then used to train a neural network model. Once trained, the model can detect anomalies and identify types of nail infections with high accuracy. The implementation of this technology is expected to expedite the diagnostic process, reduce human error, and improve access to healthcare services, particularly in areas with a shortage of trained medical personnel [15][16].

The urgency of research in personal hygiene and nail diseases is exceptionally high due to the significant health implications of untreated nail infections, which can range from minor discomfort to severe systemic health issues. Conducting in-depth research not only aids in identifying risk factors, transmission patterns, and effective prevention strategies but also supports the development of evidence-based interventions. These interventions are crucial for designing educational programs and health campaigns aimed at raising public awareness of the importance of proper nail care [17]. This study specifically focuses on leveraging advanced deep learning techniques, particularly Convolutional Neural Networks (CNNs), to address the challenges of nail condition detection [18][19]. By introducing an efficient and accessible diagnostic tool, this research contributes uniquely to the field by bridging the gap between technological advancements and practical healthcare applications, ultimately improving early diagnosis and treatment outcomes. In Indonesia, collaboration between the government, healthcare institutions, and the community is essential for implementing effective prevention and treatment strategies to address nail diseases [20][21]. Appropriate research and interventions can help reduce the prevalence of these conditions, thereby improving public health and well-being. The urgency for research and the application of deep learning technology for nail disease detection in Indonesia is particularly high [22]. With the relatively high prevalence of nail infections and limited access to healthcare services in many areas, technology-based solutions have the potential to become transformative [23]. This study aims to enhance the quality of diagnosis and provide valuable data for developing more effective prevention and treatment strategies. By integrating this approach into user-friendly applications, individuals can perform preliminary self-assessments before consulting medical professionals. This research highlights the importance of leveraging academic and technological advancements to deliver accessible and impactful healthcare solutions.

2 Method

2.1 Dataset collection

This research adopts the Convolutional Neural Network (CNN) method to detect nail images. This research flow is divided into two main stages, namely the Training and Testing stages. The research begins with the collection of nail image datasets as in Figure 1 which are obtained open access in https://www.kaggle.com/datasets/saisrushikgovindgari/nail-disease-dataset, in Table 1 this dataset is a set of nail images that have 17 classes with a total of 655 images and have been separated into training data and testing data, the folder will be used in the training and testing process of the CNN model.

Table 1. Setting Word's Margins

No.	Class Disease	Total
1.	Darier Disease	47
2.	Muehrcke Lines	33
3.	Aloperia Areata	47
4.	Beau Lines	42
5.	Bluish Nail	50
6.	Clubbing	40
7.	Eczema	45
8.	Half nail	38
9.	Koilonychia	38
10.	Leukonychia	31
11.	Onycholysis	50
12.	Pale Nail	35
13.	Red Lunula	15
14.	Splinter Hemorrhage	62
15.	Terry Nail	36
16.	White Nail	19
17.	Yellow Nail	27
Total Citra		655
Training		524
Testing		131

Fig. 1. Dataset collected samples.

2.2 Pre-processing data

Before entering the training stage, the nail image data first goes through a pre-processing stage. The pre-processing stage is an important step in data processing before the data is used to train the CNN model [19]. One of the steps in pre-processing is resizing the image. In this study, the uniformed image was made into 224x224 resolution as in Figure 2. The purpose of resizing the image is to equalize the dimensions of the images in the dataset so that the

model can process them efficiently. This process also helps reduce computational complexity as smaller images require less memory and processing power. With uniform image sizes, the model can focus more on the patterns present in the data without being distracted by size differences that may cause bias in learning.

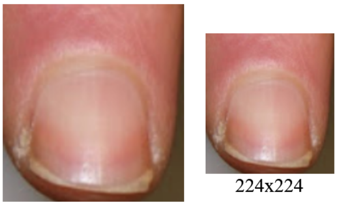

Fig. 2. Pre-processing data sample.

2.3 Processing data

The test training stage, often referred to as the training and testing stage, is a critical step in the development of machine learning models. The purpose of this stage is to teach the model to recognize patterns in the data and then evaluate the model's capabilities. The main objective of the test training stage is to train the model using a prepared dataset. The model learns from the data by adjusting its weights and biases to minimize the prediction error. This process allows the model to recognize patterns and relationships in the data so that it can make accurate predictions on new data [8]. In this research, the training stage to train the CNN model uses a dataset that has been pre-processed. The steps at this stage are as follows:

a. Training Using CNN Method: The CNN model is trained with the nail image dataset.
b. Evaluation of Accuracy Results: After training, the model is evaluated to see how accurate the predictions are. If the accuracy results are not sufficient, the training process is repeated with adjusted parameters until satisfactory accuracy results are obtained. The CNN model that has been trained with satisfactory accuracy is then saved to be used in the testing phase.

This is a separate test that is not used during training. This test aims to evaluate the model's ability to make correct predictions on data that has never been seen before. The results of this test provide an idea of how well the model is reliable in real-world situations. In this research, the testing stage is to test the performance of the CNN model in detecting nail images on new data. The steps at this stage are as follows:

a. Detection Using CNN: The trained CNN model is used to detect the nail image in the test dataset.
b. Nail Image Detection Results: The results of this detection are analyzed to evaluate the performance of the model in real conditions.

After the testing process is complete, the research ends by obtaining the results of nail image detection which is expected to be applied in related fields.

2.4 Model evaluation

Convolutional Neural Network (CNN) is a type of deep learning architecture specifically designed for processing data that has grid patterns, such as images. CNNs have proven to be very effective in pattern recognition and image classification tasks. The CNN architecture consists of several layers, each of which has a specific role in processing and extracting features from the input data [9]. A typical CNN is shown in Figure 3.

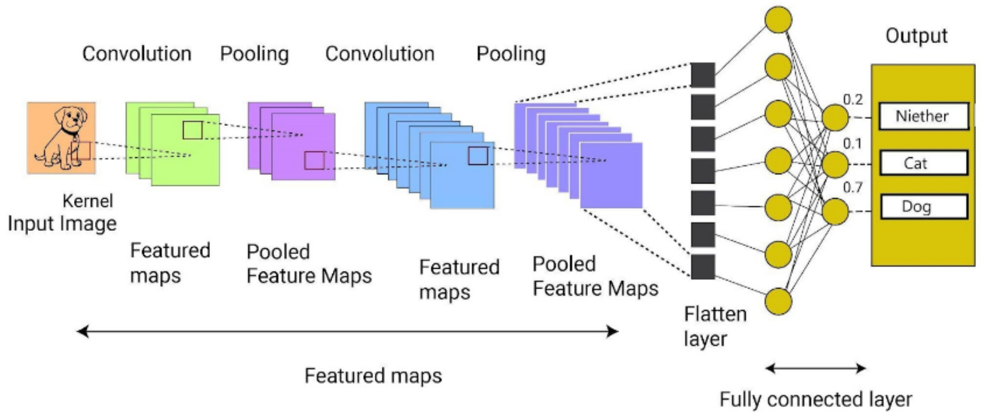

Fig. 3. CNN model diagram.

Refer to Figure 3, the following information about CNN model diagram:

a. Convolutional Layer, this layer is the core of the CNN. Here, small-sized filters (or kernels) perform convolution operations on the input data to extract local features such as edges, texture, or color.
b. Activation Layer, after convolution, an activation function such as ReLU (Rectified Linear Unit) is applied to add non-linearity into the model, which helps in capturing complex relationships in the data.
c. Pooling Layer, this layer is used to reduce the spatial dimension of the extracted features, reducing the number of parameters and computation in the network. Max pooling is one of the most commonly used pooling methods.
d. Fully Connected Layer, at the end of the network, the extracted features are flattened into vectors and passed through several fully connected layers to perform classification or regression.

The mechanism by which the CNN process works, an input image is provided to the CNN network. This image typically has dimensions of height x width x color channel (e.g., 32x32x3 for RGB images). After the input image Convolutional and Pooling Operations, the image goes through multiple convolution and pooling layers. Each convolution layer applies filters that extract specific features from the image. The pooling layer then reduces the dimension of the features to reduce computational complexity. Furthermore, after multiple convolution and pooling layers, the end result is a three-dimensional tensor that is converted into a one-dimensional vector (flattening) to be processed by the fully connected layers. Finally, Fully Connected Layers, the flattened feature vector passes through multiple fully connected layers that perform the classification task. The last layer often uses a softmax activation function to assign class probabilities.

CNN is a very powerful method in deep learning, especially for tasks involving visual data. With their ability to automatically extract features from raw data and reduce the need for manual preprocessing, CNNs have become a standard in image processing and pattern recognition. The combination of convolution, activation, pooling, and fully connected layers allows CNNs to capture and process information in a highly efficient and accurate manner [17].

3 Result and Discussion

In deep learning, especially in Convolutional Neural Networks (CNNs), configuration parameters play a crucial role in determining how the model processes and learns from data. Each parameter influences the model's performance and its ability to perform tasks such as image classification, segmentation, and object detection. The CNN architecture and its corresponding parameters used in this study are detailed in Table 2.

Table 2. CNN model parameters.

Configuration	Value
Total Parameter	14.862.275
Train Parameter	147.587
Dense	99
Image Size	224
Batch Size	128
Epoch	100
Optimizer	Adam
Learning Rate	0.001
Dropout Rate	0.2
Activation	ReLU
Pooling	Average

The following explanation about CNN model parameters in Table 2 are:

1. The total parameters in the model indicate the overall number of weights and biases to be trained in the network. With a total of 14,862,275 parameters, this indicates that the model has many complex layers and/or filters. The large number of parameters allows the model to learn highly complex and detailed features from the data, but it also requires high computational capacity and can be susceptible to overfitting if not managed properly.
2. Train parameters of 147,587 indicate the number of parameters that will be updated during the training process. This is usually smaller than the total parameters because some parameters may have been initialized or frozen before. This setting is important for controlling model complexity and reducing overfitting, especially on data that is not very large.
3. The dense layer with the number of neurons 99 indicates that after the convolution and pooling layers, the data will be passed to the fully connected layer with 99 units. This layer serves to combine the features that have been studied by the convolution layer into a final prediction. The selection of this number of neurons depends on the complexity of the task being performed, for example multi-class classification.
4. The input image size of 224x224 pixels is a common standard in many modern CNN architectures. This size is large enough to capture significant details in an image but can still be processed in a reasonable amount of time by modern computing hardware. This image size helps in the evaluation standard and allows the use of pre-trained models.
5. A batch size of 128 refers to the number of data samples processed at once in one iteration of the training. Large batch sizes can improve computing efficiency because they take advantage of parallelism in the GPU, but they also require more memory. The choice of this batch size is a trade-off between training speed and memory usage.
6. The number of epochs of 100 indicates the number of times the entire dataset will be passed during training. More epochs allow the model to learn deeper from the data, but it also increases the risk of overfitting. Therefore, it is important to monitor the

model's performance on validation data to determine when training should be stopped.

7. Adam's optimizer is used to update the weights in the network. Adam is a popular optimization method because it combines the advantages of two other methods: AdaGrad and RMSProp. It provides an advantage in fast and stable convergence, and is able to handle adaptive learning rates.
8. A learning rate of 0.001 is a parameter that controls the size of the steps the model takes when updating its weights. This learning rate is a commonly used starting value because it provides a good balance between convergence speed and training stability. A learning rate that is too large can cause the model to be unstable, while a learning rate that is too small can slow down the training process.
9. A dropout rate of 0.2 indicates that 20% of the neurons will be dropped during training for each iteration. This technique is used to prevent overfitting by reducing co-adaptation between neurons in the tissue. Dropouts make the model more robust and improve generalization capabilities.
10. The activation function of ReLU (Rectified Linear Unit) is used to introduce non-linearity in the network. ReLU is a popular choice because it is simple and effective, helps in solving gradient vanishing problems, and allows the network to learn non-linear relationships quickly.
11. Average pooling is used to reduce the dimension of map features after the convolution layer. Unlike max pooling which only takes the maximum value, average pooling calculates the average of the values in the pooling window. This can be more informative in some cases, especially when information on an entire area is important for the task at hand.

While Table 2 provides key configuration parameters, further details of the CNN architecture are critical for replication and evaluation. The architecture consists of multiple convolutional blocks, each followed by ReLU activation and pooling layers. The convolutional layers extract spatial features, while the pooling layers reduce dimensionality. The final feature map is flattened and passed to a fully connected dense layer with 99 neurons for classification. The model also incorporates residual connections between certain layers to enhance gradient flow and stability during training. Data augmentation techniques, including random rotations, flips, and zooms, were applied to increase dataset variability and improve generalization. The model's training and validation performances are summarized in Table 3, which compares training and validation accuracies as well as error metrics.

Table 3. CNN model.

Epoch	Accuracy	Accuracy Validation	Error	Error Validation
1	0.3556	0.9556	1.3619	1.0097
2	0.5222	0.9556	0.9805	0.9917
3	0.6278	0.9556	0.8947	0.9365
4	0.8000	0.9556	0.7600	0.7860
5	0.7944	0.9556	0.6730	0.7280
6	0.8556	0.9556	0.5809	0.8172
…..	…..	…..	…..	…..
100	1.0000	1.0000	0.0235	0.1037

The epoch indicates the number of iterations in which the entire dataset has been processed by the model. In the table, the training results were measured at the first few epochs and the last epoch of 100. In deep learning training, each epoch gives the model the opportunity to learn from the data more deeply, adjusting the weights to minimize errors.

Accuracy shows the percentage of correct predictions on the training data after each epoch. The accuracy of the model on training data increased consistently, averaging at 99%. This steady improvement indicates that the model effectively learned the relationships within the training data, thereby enhancing its classification performance. The model demonstrated stable validation accuracy, averaging 97%. This indicates that the model generalizes well, applying its knowledge to unseen data with minimal overfitting a critical requirement for robust performance. Errors in the training data decreased over time, averaging 4%. This reflects the model’s ability to optimize its weights and reduce the loss function during training, leading to improved accuracy. The validation error averaged at 2%, with minor fluctuations across epochs. This decline demonstrates the model’s capacity to learn and minimize errors on unseen data, underscoring its generalization capability. Figure 4 illustrates the trends in accuracy and error metrics over epochs, showing a clear reduction in errors alongside improved accuracy. The graph emphasizes the effectiveness of the training process in stabilizing the model's performance, for more detail can be seen in Figure 4.

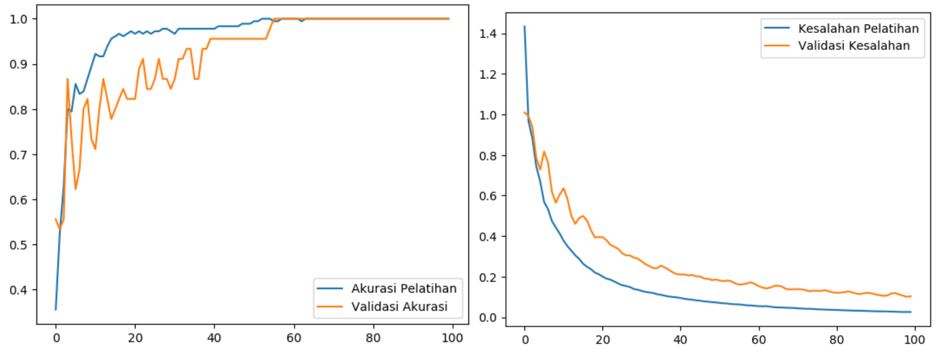

Fig. 4. CNN model result.

Furthermore, the author conducted a testing stage using the Convolutional Neural Network (CNN) model aiming to analyze and detect nails, in this case focusing on the detection of nail diseases. CNN models are one type of deep learning that is highly effective in visual pattern recognition and image classification because of its ability to capture important features of images through layers of convolution and pooling. In this context, nail images are taken and analyzed using a pre-trained CNN model with a diverse dataset of nail images, including various nail health conditions such as normal nails, yellow nails, moldy nails, and others according to the class of the dataset that has been trained. The main purpose of this test is to provide an initial diagnosis of nail health conditions based on the color and texture detected in the image. When users utilize this app, they simply take or upload an image of their nails, which will then be processed by the CNN model. The model will analyze the images, extract important features, and then compare them with patterns that have been learned during the training phase. The results of this analysis will provide an output in the form of a percentage probability regarding the condition of the detected nails. The test used 10 random images from the entire class so that there were 170 images, the test detection was carried out as shown in Table 4.

Table 4. CNN Model Detection Accuracy

No.	Class	True	False
1.	Darier Disease	7	3
2.	Muehrcke Lines	10	0
3.	Aloperia Areata	8	2
4.	Beau Lines	9	1
5.	Bluish Nail	6	4
6.	Clubbing	9	1
7.	Eczema	10	0
8.	Half nail	8	2
9.	Koilonychia	9	1
10.	Leukonychia	10	0
11.	Onycholysis	7	3
12.	Pale Nail	5	5
13.	Red Lunula	6	4
14.	Splinter Hemorrhage	10	0
15.	Terry Nail	8	2
16.	White Nail	9	1
17.	Yellow Nail	10	0
Total		141	29

The results of the nail detection test using the Convolutional Neural Network (CNN) model in Figure 5 provide in-depth insight into the model's ability to recognize various nail conditions based on the images provided. According to Table 4, it shows the detection accuracy of different classes of nail conditions, as shown in the table. The CNN model has been tested against 17 different classes of nail conditions, ranging from Darier Disease to Yellow Nail. In each class, the model successfully detects conditions with varying degrees of accuracy. For example, for the "Darier Disease" class, the model correctly detected 7 times and made a mistake 3 times. Similarly, for "Muehrcke Lines," the model recorded 10 true detections and no false detections. Lower results were seen in some classes such as "Pale Nail," where the model only managed to correctly detect 5 times and get it wrong 5 times. This suggests that some nail condition classes may be more difficult for models to recognize, perhaps due to greater visual variation or a lack of adequate training data for those classes. However, there are also classes that show excellent performance, such as "Splinter Hemorrhage" with 10 correct detections and no detection errors, and "White Nail" which records 9 correct detections and 1 error. This shows that the CNN model is quite effective in recognizing certain visual patterns that often appear in some nail conditions. This gives an indication that while the model is quite effective, there is still room for improvement especially in terms of detection accuracy of 83%. The following is the level of accuracy of the CNN model calculated by the equation (1).

$$Accuracy\ (\%) = \frac{\Sigma\, Total\ true\ prediction}{\Sigma\, Total\ prediction} \times 100\% \tag{1}$$

$$Accuracy\ (\%) = \frac{141}{170} \times 100\% = 83\% \tag{2}$$

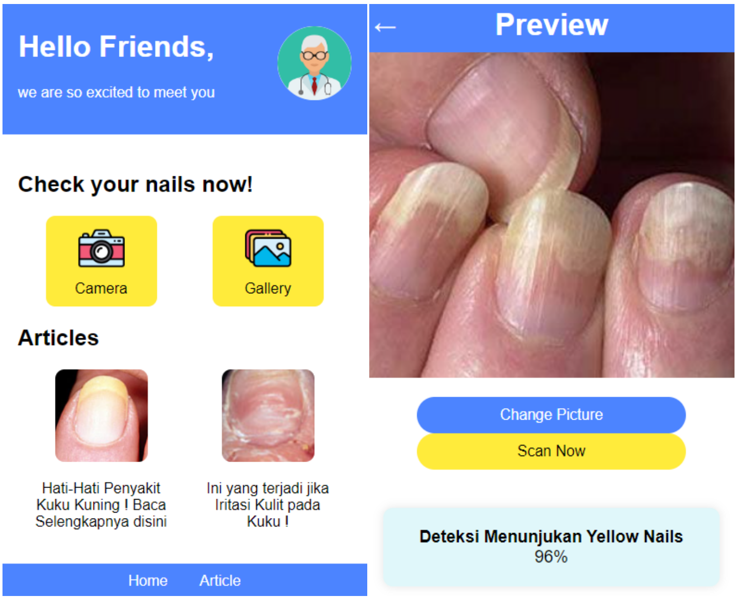

Fig. 5. CNN model testing result (app in Indonesian).

Figure 4 illustrates the trends in training and validation accuracy and errors over epochs. The graph reveals a consistent increase in accuracy and a corresponding decline in errors, demonstrating effective learning. The stability of validation metrics relative to training metrics further confirms the model's ability to generalize well. Figure 5 visually represents the detection results across various nail condition classes. It highlights classes where the model excels (e.g., "Splinter Hemorrhage") and those needing improvement (e.g., "Pale Nail"), providing actionable insights for enhancing model performance. Key Insights and Recommendations High accuracy for well-defined classes like "Splinter Hemorrhage" and "Muehrcke Lines." Stable validation metrics indicate strong generalization capabilities effective use of CNN architecture for extracting and analyzing visual patterns in nail images. Areas for Improvement classes with lower accuracy, such as "Pale Nail," require additional training data to address variability in visual features. Model parameters, including dropout rates and convolutional layer configurations, may need optimization to enhance sensitivity to subtle features. Future Directions enhanced Dataset Diversity: Expand the training dataset to include more images for underrepresented classes, improving the model's ability to generalize. Advanced Data Augmentation apply techniques such as rotations, flips, and zooms to artificially increase dataset variability. Real-World Testing Validate the model with clinical datasets to ensure reliability in practical applications. This study demonstrates the potential of CNN models in medical applications for nail condition detection. While the current model achieves an impressive 83% accuracy, targeted improvements in dataset diversity, parameter optimization, and real-world validation can further enhance performance. These advancements will not only improve detection accuracy but also make this technology more accessible and effective for early diagnosis in healthcare applications.

4 Conclusion

This study explored the application of Convolutional Neural Networks (CNNs) to detect 17 classes of nail conditions, achieving an overall detection accuracy of 83%. The CNN model, configured with predefined parameters such as a dropout rate of 0.2 and a learning rate of 0.001, demonstrated strong generalization capabilities. Notably, the dropout rate effectively reduced overfitting by introducing regularization, while the learning rate balanced convergence speed and stability during training. These parameter choices were instrumental in achieving a low validation error (0.1037) compared to training error, highlighting the model's ability to generalize to unseen data. Certain classes, such as "Leukonychia" and "Splinter Hemorrhage," showed excellent detection accuracy due to well-defined visual patterns in these conditions. However, classes like "Pale Nail" and "Alopecia Areata" exhibited lower accuracy, indicating the need for additional data and refinement in feature extraction. This highlights the model's strengths while also identifying areas requiring further research. The results underscore the potential of using CNN models in medical applications, providing a rapid and accessible diagnostic tool for nail condition detection.

While this study demonstrates the potential of CNN models in detecting nail conditions with an accuracy of 83%, further refinements can enhance performance and usability. To address specific challenges, the following improvements are recommended, Enhanced Dataset Diversity: Expanding the training dataset with a focus on underrepresented classes, such as "Pale Nail" and "Alopecia Areata," will help the model better recognize subtle and complex patterns. Fine-Tuning Parameters: Further optimization of parameters like dropout rate and learning rate can ensure a balance between model robustness and accuracy. These refinements can enhance the generalization capabilities observed in this study. Data Augmentation: Introducing techniques such as rotation, flipping, and zooming will provide additional variability in the training data, improving the model's resilience to diverse input scenarios. Real-World Testing: Evaluating the model with clinical datasets from varied environments will validate its applicability in practical medical settings, ensuring it performs reliably beyond controlled experiments. User-Centric Interface: Developing a simple and intuitive application interface will ensure the technology is accessible to a broader audience, providing timely and reliable preliminary diagnoses. These refinements will build upon the strengths of this research, ensuring its continued value in medical applications while addressing areas with room for improvement. By doing so, the CNN model can contribute significantly to advancing healthcare accessibility and accuracy.

References

1. M. Galluzzo, M. Talamonti, A. Cioni, V. Maffei, R. G. Shumak, L. Tofani, L. Bianchi, and E. Campione, Efficacy of tildrakizumab for the treatment of difficult-to-treat areas: scalp, nail, palmoplantar, and genital psoriasis. J. Clin. Med. **11**, 9 (2022).
2. C. for D. C. and Prevention, Healthy Habits: Nail Hygiene. Water, Sanitation, and Environmentally Related Hygiene (WASH).
3. G. S. Kaeley, L. Eder, S. Z. Aydin, P. Rich, and C. J. Bakewell, Nail psoriasis: Diagnosis, assessment, treatment options, and unmet clinical needs. J. Rheumatol. **48**, 1208–1220 (2021).
4. P. M. D. Investama, Bukan Cuma Estetika, Ini Pentingnya Menjaga Kebersihan Kuku. Halodoc.
5. S. Gregoriou, N. Mpali, G. Vrioni, E. Hatzidimitriou, S. E. Chryssou, and D. Rigopoulos, Epidemiology of onychomycosis in an academic nail unit in south greece during a three-year period. Skin Appendage Disord. **6**, 102–107 (2020).

6. E. S. Majawati, J. Kurniawati, and M. P. Sari, Prevalence of onychomycosis in fish traders in Kopro Market West Jakarta. Master Thesis, Universitas Indonesia, Indonesia (2019).
7. I. An, M. Harman, and I. Ibiloglu, Topical Ciclopirox Olamine 1%: Revisiting a Unique Antifungal. Indian Dermatol. Online J. **10**, 481–485 (2021).
8. J. Abdulhadi, A. Al-Dujaili, A. J. Humaidi, and M. A. R. Fadhel, Human nail diseases classification based on transfer learning. ICIC Express Lett. **15**, 1271–1282 (2021).
9. M. A. Chessa et al., Pathogenesis, Clinical signs and treatment recommendations in brittle nails: a review. Dermatol. Ther. **10**, 15–27 (2020).
10. A. Kyriakou, S. C. Zagalioti, M. G. Trakatelli, C. Fotiadou, Z. Apalla, E. Lazaridou, and A. Patsatsi, Fungal infections and nail psoriasis: an update. J. Fungi **8**, 1–9 (2022).
11. S. Muddasani, G. Lin, J. Hooper, and S. B. Sloan, Nutrition and nail disease. Clin. Dermatol. **39**, 819–828 (2021).
12. Kemensos RI, Penguatan kapabilitas anak dan keluarga Perilaku Hidup Bersih Dan Sehat (PHBS) adalah upaya untuk memperkuat budaya seseorang, kelompok maupun masyarakat agar peduli dan mengutamakan kesehatan untuk mewujudkan kehidupan yang lebih baik.
13. Y. K. A. Norma Farizah Fahmi, D. A. Anggraini, Onikomikosis merupakan infeksi pada lempeng kuku yang dapat disebabkan oleh jamur dermatofita. J. Kesehatan Masyarakat **1**, 123 (2021).
14. Kementrian Kesehatan, Gerakan PHBS sebagai langkah awal menuju peningkatan kualitas kesehatan masyarakat.
15. Ivonne Ruth Situmeang, J. Tobing, M. Simanjuntak, P. Tobing, and S. B. Hutagalung, Penyuluhan Perilaku Hidup Bersih dan Sehat (PHBS). Ikra-Ith Abdimas **8**, 240–243 (2024).
16. R. A. Tilasefana and R. E. Putra, Penerapan metode deep learning menggunakan algoritma CNN dengan arsitektur VGG NET untuk pengenalan cuaca. J. Informatics Comput. Sci. **05**, 48 (2023).
17. M. Yuliana, Aplikasi diagnosa infeksi jamur pada kuku kaki manusia dengan menggunakan metode agile development. J. SANTI - Sist. Inf. Dan Tek. Inf. **2**, 79–86 (2023).
18. H. Istiqomah and R. Ardianto, Prediksi kanker darah menggunakan metode Convolutional Neural Network. **4**, 51–60 (2024).
19. M. Works, Deep Learning in MATLAB.
20. D. L. Hidup, Pentingnya kesadaran masyarakat akan kebersihan. Artikel Lingkungan Hidup.
21. R. Ardianto and S. Kartika Wibisono, Analisis Deep Learning Metode Convolutional Neural Network Dalam Klasifikasi Varietas Gandum. J. Kolaboratif Sains **6**, (2023).
22. S. Ch. A. W. Sutjipto, Y. Wijoyo, and N. Priyatni W., Pengembangan Media Edukasi Berbasis Video Perilaku Hidup Bersih dan Sehat (PHBS) dan Penggunaan Multivitamin Untuk SMK Kesehatan di Yogyakarta. Majalah Farmaseutik **18**, 17 (2022).
23. Niki Nadialita, A. Anhar, and A. M. Muslih, Analisis Perubahan Tutupan Lahan Kesatuan Hidrologi Gambut Krueng Wonki-Krueng Gubon di Kabupaten Aceh Barat. J. Ilmiah Mahasiswa Pertanian **8**, 4 (2023).