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Integration of YOLOv8 and FastAPI for Early Detection of Nail Diseases

Ferdinand Linggo Pakpahan[1)], Joni Satrio Sembiring[2)],Tivanez Ballerina Abellista[3)], Evta Indra[4)*]
[1*,2,3,4)]Universitas Prima Indonesia, Indonesia
[1)]dinandpakpahan7@gmail.com, [2)]jonisatrio2003@gmail.com, [3)]tvnzblrna@gmail.com,
[4*)]evtaindra@unprimdn.ac.id

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Abstract: Nails are important indicators of various health conditions, including fungal infections (onychomycosis), autoimmune disorders (psoriasis), and subungual melanoma (black line). However, early detection of these diseases remains limited due to low accessibility and public awareness. This study aims to develop an end-to-end, web-based early detection system for nail diseases by integrating the YOLOv8 object detection algorithm with the FastAPI framework. A total of 600 annotated nail images obtained from Kaggle were categorized into four classes: healthy nail, psoriasis, black line, and onychomycosis. The model was trained using PyTorch on Google Colab with GPU acceleration and evaluated using precision, recall, and mean Average Precision (mAP@0.5). The model achieved a precision of 93%, recall of 88%, and mAP@0.5 of 89%. Manual testing on 100 images via the deployed web application showed an overall accuracy of 97%. Class-wise accuracy reached 100% for healthy nail and psoriasis, 92% for black line, and 96% for onychomycosis. These results demonstrate that the system performs reliably across various conditions. The main contribution of this study is the implementation of a real-time, web-integrated nail disease detection system that is accessible to both medical professionals and the general public. Future research may focus on expanding the dataset, optimizing model robustness under varied lighting and background conditions, and conducting clinical validation.

Keywords: YOLOv8, early detection, FastAPI, object detection, web-based

INTRODUCTION

Nails serve as both physical protection for the fingertips and early indicators of various health conditions, ranging from minor infections to serious systemic diseases. Visual changes in nail texture, color, or shape may reflect underlying conditions; for instance, black lines can indicate subungual melanoma(Ito et al., 2023). Onychomycosis is a common fungal infection of the nails(Gupta et al., 2022) and nail psoriasis is often characterized by abnormal, pitted nail surfaces(Hadeler et al., 2021), all of which differ significantly from healthy nails.

Despite the diagnostic value of nail appearance, early detection of nail-related diseases remains limited by factors such as low public awareness and unequal access to dermatological services(Mahajan, 2024a). This underscores the need for accessible, automated tools that can assist in the early identification of nail abnormalities.

Recent developments in artificial intelligence (AI), particularly in the areas of computer vision and deep learning, have enabled more accurate and efficient image-based disease classification(Flores et al., 2021). Object detection models such as YOLO (You Only Look Once) have been widely applied in medical imaging due to their speed and accuracy(Kitsiranuwat et al., 2023). However, the majority of existing studies focus on classification models that require cropped and preprocessed images, rather than detecting and localizing disease regions directly. Moreover, studies focusing specifically on nail diseases using object detection approaches remain limited, especially those that integrate detection models with user-friendly web applications for real-time use(Tuncer et al., 2024).

Addressing this gap, the present study proposes a web-based early diagnosis system for nail diseases using the YOLOv8 object detection algorithm implemented in PyTorch. The model is designed to detect and classify four categories healthy nails, onychomycosis, psoriasis, and black lines directly from raw input images. Detection will be visualized using bounding boxes, providing immediate visual feedback to users. The system will be integrated into a web application using the FastAPI framework to ensure accessibility and usability for both patients and medical practitioners (Egga Naufal Daffa Tanadi et al., 2024).

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Model performance will be evaluated using standard object detection metrics such as precision, recall, and mean Average Precision (mAP) (Ali & Zhang, 2024). The effectiveness of YOLOv8 in detecting subtle visual indicators of nail disease will be compared to benchmarks from previous work.

By introducing an object detection-based approach to nail disease screening, this research contributes to the limited body of literature on AI-powered dermatological diagnostics. The integration of YOLOv8 and FastAPI offers a scalable and practical tool that supports self-screening, facilitates medical decision-making, and promotes public awareness about nail health (Albahli, 2025). In the long term, this solution can serve as a foundation for the development of mobile-based diagnostic applications in dermatology and telemedicine.

LITERATURE REVIEW

Nail disease detection using digital image-based techniques is rapidly advancing in the fields of computer vision and machine learning(Gaurav et al., 2025). Object detection algorithms such as YOLO are favored for their ability to simultaneously classify and localize objects(Shandilya et al., 2024). The latest iteration, YOLOv8, incorporates advancements like Anchor-Free Detection and Distribution Focal Loss(Achmad & Sahibu, 2024), which significantly improve accuracy, particularly for small objects like nails. Most previous studies have used whole-image classification approaches, which can reduce accuracy due to interference from background regions using cnn algorithms (Madani & Pratiwi, 2024). In contrast, object detection methods like YOLO focus specifically on the affected nail area, thus minimizing interference from other parts and using a bounding box to mark the area. (Mahajan, 2024b)

Medical applications of YOLO also demonstrate high performance. For example, (Ahadin et al., 2024)developed a brain tumor detection model using the YOLOv10 architecture on MRI images, achieving a precision of 97.88%, recall of 95.24%, and mean Average Precision (mAP50) of 95.84% at the 200th epoch. In nail disease detection, reported an 87.8% accuracy in binary classification of healthy versus unhealthy nails, outperforming conventional classification methods that typically achieve around 80%. However, YOLO's application in nail disease detection remains limited, especially in real-time, web-based implementations. This research aims to develop a YOLOv8-based nail disease detection system integrated with a FastAPI web application, offering users easier and more responsive access to early screening tools.(Cengil, 2024).

METHOD

Research Flow

This research is a quantitative research type. This study aims to evaluate the effectiveness of the *YOLO* algorithm in detecting nail diseases through image analysis. The detection model is integrated into a web application using the *FastAPI* framework, allowing users to perform automated and fast detection through a web interface. The system's performance is measured using quantitative evaluation metrics such as accuracy, precision, recall, and F1-score to ensure reliable results. To get an overview of the research we conducted, it can be seen in figure 1.

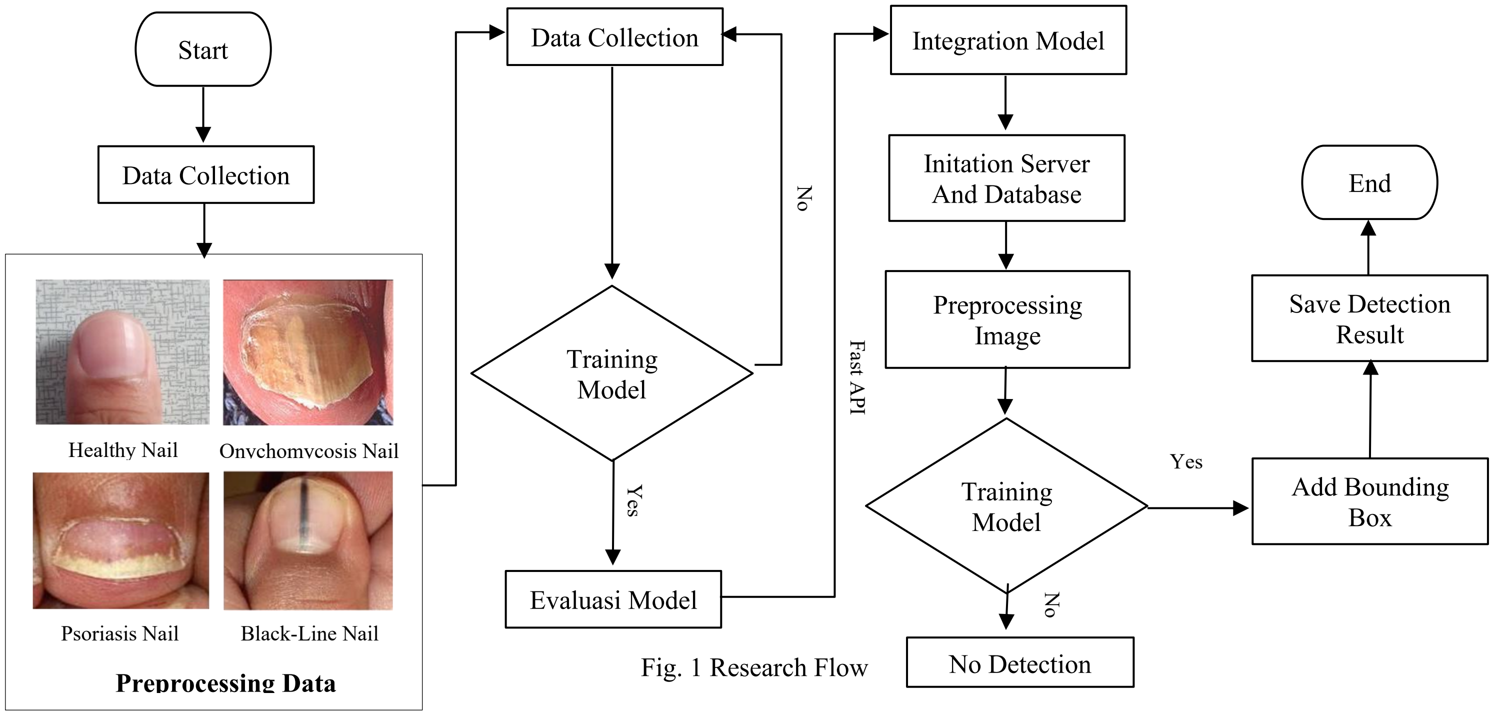

Fig. 1 Research Flow

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Data Collection

The dataset used in this study was obtained from the *Kaggle* by Joseph Rasanjana. It consists of 600 nail images evenly distributed across four classification categories: black line, psoriasis, and onychomycosis with each class containing 150 images. This classification aims to detect various nail conditions, including diseases often overlooked due to a general lack of awareness regarding proper nail health care. Shown in figure 2.

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

Fig. 2 Dataset (a) Black Line; (B) Healthy Nail; (c) Psoriasis; (d) Onychomycosis

Preprocessing Data

Data preprocessing was conducted to ensure consistency in the format and quality of the images used for training and testing the model. All images were resized to 224 × 224 pixels to match the model's input requirements and normalized to a pixel value range of 0 to 1 to accelerate the training process and enhance model stability. Prior to training, a data labeling process was carried out using Roboflow, a web-based annotation tool that allows manual bounding box annotation and class assignment. Each image was labeled into one of four target classes: Black Line, Healthy Nail, Psoriasis, or Onychomycosis, following a multi-class single-label classification approach.

After labeling, the dataset was divided into three parts with a ratio of 70% for training, 15% for validation, and 15% for testing. To increase the diversity of the training data and reduce the risk of overfitting, data augmentation techniques such as image rotation, horizontal flipping, and contrast enhancement were applied. These techniques enabled the model to better recognize various nail conditions in diverse real-world scenarios.

Yolov8 Architecture

YOLOv8 represents the latest advancement in the You Only Look Once (*YOLO*) series of object detection models developed by the *Ultralytics* team, known for its exceptional speed and accuracy in real-time detection tasks. Unlike traditional approaches that rely on computationally intensive sliding window techniques, *YOLOv8* treats object detection as a single regression problem by predicting bounding boxes and class probabilities directly from an input image in one forward pass, resulting in faster and more efficient detection. The architecture consists of three main components: the *Backbone*, which uses a custom CSPDarknet53 to extract features with improved information flow through cross-stage partial connections; the *Neck*, which replaces the traditional Feature Pyramid Network (FPN) with a novel C2f module that effectively merges semantic and spatial features across scales to enhance accuracy—particularly for small objects; and the *Head*, which is responsible for making predictions by outputting bounding boxes, objectivity scores, and class probabilities across multiple detection modules, ultimately producing the final detection results(Mehra, 2024). Shown in figure 3.

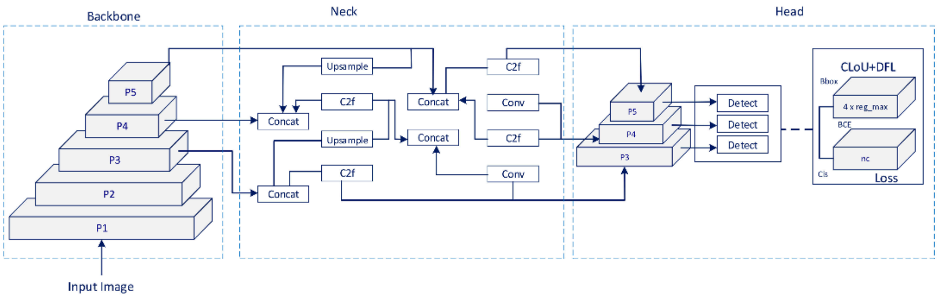

Fig. 3 Architecture YOLOv8

Training Model

The training process of the *YOLOv8* model serves as a critical step in this research. During this stage, the system is trained using the prepared dataset to learn and identify patterns related to nail conditions. If the results show unsatisfactory performance, such as low precision or high error rates, the process will return to the architectural design phase to revise the model structure or adjust relevant parameters. Once optimal performance

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is achieved, indicated by reliable and consistent evaluation metrics, the model proceeds to the next phase, which is integrated into a web application using the *FastAPI* framework for real-time implementation.

Model Evaluation

The model evaluation in this study was carried out to assess the performance of the *YOLOv8* algorithm in detecting nail diseases. Testing was conducted using a separate test dataset, and the results were analyzed using standard quantitative metrics; accuracy, precision, recall, and F1-score. Accuracy measures how well the model correctly classifies all instances, while precision reflects how many predicted positive cases are correct. Recall indicates the model's ability to identify all relevant positive cases, and the F1-score provides a balanced measure between precision and recall, which is especially useful when dealing with imbalanced data. This evaluation helps ensure that the model is fast and reliable in producing accurate detection results.

$$Precision = \frac{TP}{TP+FN} \tag{1}$$

To determine the precision, equation (1) is used. Precision represents the proportion of correctly predicted positive observations out of all predicted positives.

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

Recall, as described in equation (2), reflects the model's ability to retrieve all relevant positive instances. It is obtained by dividing the true positive count by the total of true positives and false negatives.

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \tag{3}$$

The formula used to calculate accuracy is shown in equation (3), where the values is derived by dividing the sum of true positives (TP) and true negatives (TN) by the total number of instances, including false positives (FP) and false negatives (FN).

$$F1\ Score = 2 \times \frac{Recall \times Precision}{Recall+Precision} \tag{4}$$

The F1-score, or F-measure, provides a single metric that balances both precision and recall. It is computed as the harmonic mean of two values using equation.

Model Integration Using FastAPI

Integrating the detection model using *framework* provides an efficient and scalable solution for deploying AI in healthcare applications. *FastAPI*, a modern web framework built with Python, is well known for its high performance and simplicity, making it ideal for serving machine learning models. In this project, *framework* is used to build a web-based interface that allows users to upload nail images and receive instant diagnostic results(Gautam Bharadwaj, 2025). The backend processes include image preprocessing, model inference using *YOLOv8*, and returning predictions with confidence scores and bounding boxes. *FastAPI's* asynchronous nature ensures smooth performance, even with multiple user requests. This integration not only improves accessibility for both medical professionals and the public but also supports future developments such as mobile diagnostics, telemedicine platforms, and integration with health record systems, contributing to smarter, AI-driven healthcare services.

To provide a clearer understanding of how the detection model is integrated into FastAPI, Figure 4 illustrates the system architecture. This diagram illustrates the interactions between client-side user requests, backend processing, and transfer of detection results to the database. This architecture aims to ensure timely, accurate, and accessible detection via a web browser. Even the pseudocode of the API development process can be seen below to illustrate how the system works.

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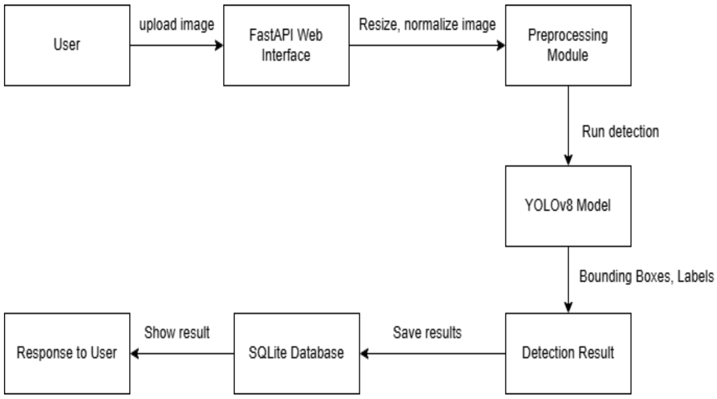

Fig. 4 System Architecture and API Design

API Endpoint for Image Upload and Detection

```
@app.post("/upload", response_class=HTMLResponse)
async def upload(request: Request, file: UploadFile = File(...)):
upload_path = f"static/uploads/{file.filename}"
with open(upload_path, "wb") as buffer:
shutil.copyfileobj(file.file, buffer)
result_filename = predict_and_plot(upload_path, "static/results")
# Save to database
insert_history(file.filename, result_filename)
history = get_history()
return templates.TemplateResponse("index.html", {
"request": request,
"result_image": f"/static/results/{result_filename}",
"now": datetime.now().timestamp(),
"history": history
})
```

Initiation Server and Database

The server is initialized using *framework* to handle user requests such as images uploads and real-time prediction processing. The system is connected to an *SQLite* database, initialized with *SQLAlchemy* to store data such as image metadata and detection results. This process includes setting up endpoints, configuring middleware, and defining database schemas to ensure efficient and responsive integration between the backend and data storage.

Preprocessing Image

The image preprocessing step involves resizing each uploaded image to 224x224 pixels. This step aims to standardize the input dimensions to match the *YOLOv8* model architecture and ensure efficient inference. The resizing process is handled on the backend using an image processing library such as Pillow (PIL), which is integrated into the *FastAPI* application. Through this preprocessing, the system can accept images of various sizes from users and process them consistently before performing detection with the model.

Model Prediction

The model prediction process in the FastAPI-based web application starts when a user uploads an image through the interface. Each uploaded image is preprocessed resized and normalized before being passed to the YOLOv8 model, which performs object detection and classification. The system follows a multi-class single-label classification approach, where each image is associated with only one label from the following categories: Healthy Nail, Psoriasis, Onychomycosis, or Black Line.If the model successfully detects a nail condition, it extracts the class label and bounding box information, which are then saved to the SQLite database. The detection results, including bounding boxes, are also visualized on the image and displayed via the web interface. However, if no objects are detected either due to healthy nails or unclear image content the system provides no diagnostic conclusion and does not store any data, ensuring that only meaningful and confident predictions are recorded.

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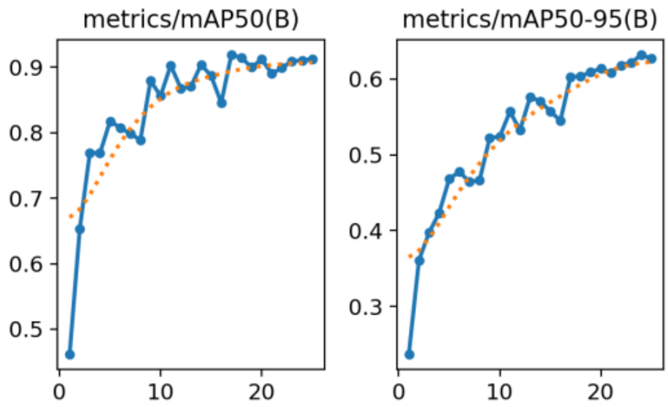
RESULT

Training Model Result

The YOLOv8 model developed in this study demonstrated effective object detection performance on nail images. The evaluation metrics included accuracy, precision, recall, and F1 score. The model successfully identified key features distinguishing different nail disease types. However, issues such as suboptimal lighting and missed detections were observed, indicating the need for further optimization through improved data preprocessing and data augmentation techniques.

Fig. 5 shows the model training result visualizations: (a) mAP@0.5 and (b) mAP@0.5:0.95. The model achieved an mAP@0.5 close to 0.9 on the validation set, indicating high accuracy in detecting objects with moderate overlap. The stricter mAP@0.5:0.95 metric also showed notable improvement, reflecting the model's robustness under challenging localization requirements.



(a) (b)

Fig. 5 Model Training Result Visualization; (a) metrics/mAP50; (b) metrics/mAP50-95

Fig. 6 presents the heatmap confusion matrix analysis. The healthy nail category achieved 92% accuracy, with most images correctly classified. Onychomycosis detection was also accurate at 90%, although some misclassifications occurred. The black line category reached 77% accuracy, with misclassifications mostly due to background interference. Psoriasis detection improved significantly compared to previous results, with only minor misclassifications into onychomycosis and background classes. Overall, the model effectively differentiated healthy from diseased nails, though challenges remain in distinguishing visually similar conditions such as black line, onychomycosis, and psoriasis.

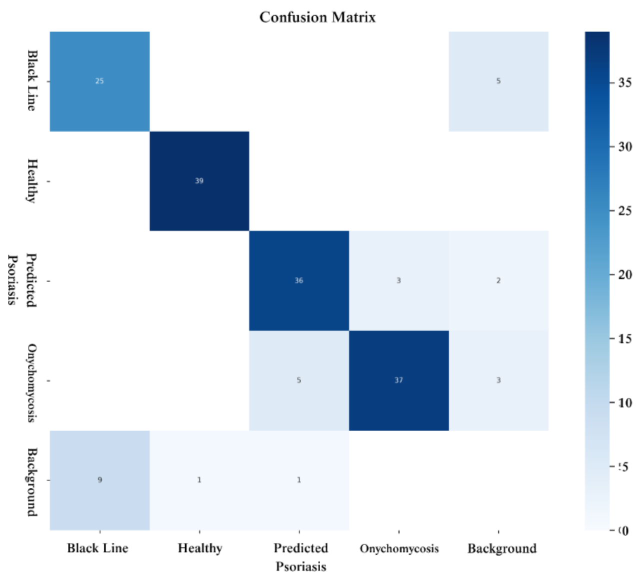


Fig. 6 Heatmap Confusion Matrix

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Fig. 7 illustrates detection results on the web application for (a) Psoriasis, (b) Onychomycosis, (c) Healthy Nail, and (d) Black Line.The YOLOv8 model achieved 97% accuracy on 100 test images. Specifically, onychomycosis was correctly detected in 24 out of 25 images; psoriasis and healthy nails were detected with 100% accuracy; and the black line category reached 92% accuracy, with misclassifications mainly caused by complex backgrounds. These results show a significant improvement over previous CNN-based classification methods, which achieved approximately 80% accuracy. The advantage of YOLOv8 lies in its ability to detect specific regions using bounding boxes, reducing interference from the background. Nonetheless, challenges persist under poor lighting conditions and for visually similar cases, especially in the black line category. Therefore, further enhancement of preprocessing and data augmentation is recommended to improve overall model performance.

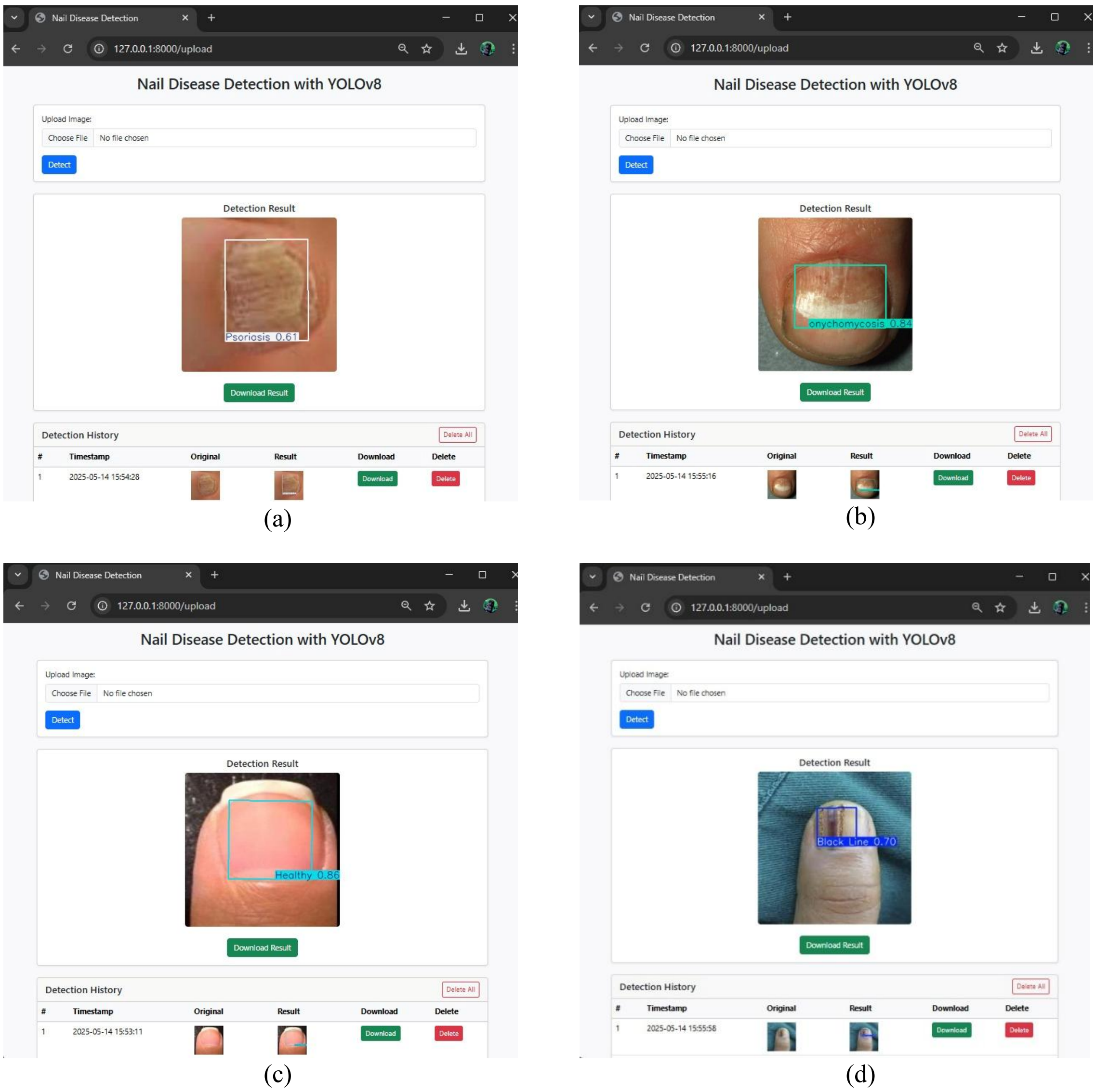

Fig. 7 Detection Results in Web (a) Psoriasis; (b) Onychomycosis; (c) Healthy Nail; (d) Black Line

DISCUSSIONS

The integration of YOLOv8 with a web-based framework shows strong potential for fast and accessible nail disease detection. Trained on 600 labeled nail images using PyTorch, the model achieved 97% accuracy, 93% precision, 88% recall, and 89% mAP@0.5, with perfect accuracy in detecting psoriasis and healthy nails.However, the limited dataset size restricts the model's generalization to diverse real-world scenarios and may introduce biases such as dominant skin tones or lighting conditions. Misclassifications in the black line category highlight challenges with background interference.Future work should expand the dataset, apply data augmentation, and explore domain adaptation to enhance robustness. Practical improvements like mobile deployment, clinical trials, and optimization for real-time inference are also recommended for wider adoption.

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CONCLUSION

This study contributes to the development of an early nail disease detection system by integrating the YOLOv8 algorithm into a web-based interface that enables accurate and real-time detection of various nail conditions. The system shows strong performance, particularly in identifying onychomycosis and healthy nails, while highlighting challenges in detecting the black line category due to background interference. It has the potential to be further developed into a mobile application and integrated into healthcare services through clinical validation and real-world optimization. With these advancements, the system can be adopted as a reliable diagnostic support tool for both healthcare professionals and the general public.

Limitations and Future Work

This study is limited by dataset size and lacks clinical validation. Future research should expand sample diversity, include real-world deployment, and conduct user testing with healthcare professionals. By addressing these limitations, future iterations of the system could enhance its diagnostic accuracy, usability, and integration within clinical workflows.

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