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Image-Based Non-Invasive Jaundice Detection Using Hybrid AI and Streamlit-Based Healthcare Application

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Abstract: *Jaundice is a medical condition caused by elevated bilirubin levels, leading to yellow discoloration of the skin and sclera. Early diagnosis is critical, especially for neonates and patients with liver disorders. Conventional diagnostic methods, such as blood tests, are invasive and require laboratory infrastructure. The proposed work introduces a system to detect jaundice non-invasively using image processing and deep learning methods embedded within a Streamlit application framework. The detection process is done by implementing a hybrid detection scheme, which uses heuristics in addition to the Convolutional Neural Network (CNN) model. In the system, real-time image capturing, preprocessing, and categorizing images as Normal, Mild, and Severe jaundice conditions is performed. In addition to the functionality discussed, other features include user authentication, report generation, AI chatbot support, and history maintenance. Results from experimentation have shown an accuracy of around 88-93%.*

Keywords: Jaundice Detection, CNN, Image Processing, AI in Healthcare, Streamlit, Non-Invasive Detection

I. INTRODUCTION

Clinically, jaundice is often the result of increased levels of bilirubin in the bloodstream. A yellow appearance is observed in the skin, eyes and mucous membranes. The prevention of complications requires prompt detection. The most common diagnostic procedures require blood tests to measure serum bilirubin, but this can be an excruciatingly painful and time-consuming process.

With the recent advances in artificial intelligence and computer vision, medical diagnosis can now be made more quickly by using images. In this study, they present a real-time jaundice detection application that employs machine learning and UI design to aid in the identification process. Additionally,

II. LITERATURE REVIEW

Several studies have explored non-invasive jaundice detection using image processing and machine learning:

Gupta et al. (2022) proposed facial image analysis techniques using color space transformations for bilirubin estimation.

Kumar et al. (2020) introduced machine learning models for neonatal jaundice detection using image datasets.

Li et al. (2022) demonstrated the effectiveness of CNNs in medical image classification tasks.

Lin et al. (2022) applied deep neural networks for automated jaundice detection with improved accuracy.

Liu et al. (2020) focused on facial image-based diagnosis using feature extraction techniques.

These studies confirm that image-based AI models can significantly reduce dependency on invasive diagnostic procedures. However, many existing systems lack real-time usability, user interaction, and deployment-ready applications, which this work addresses.

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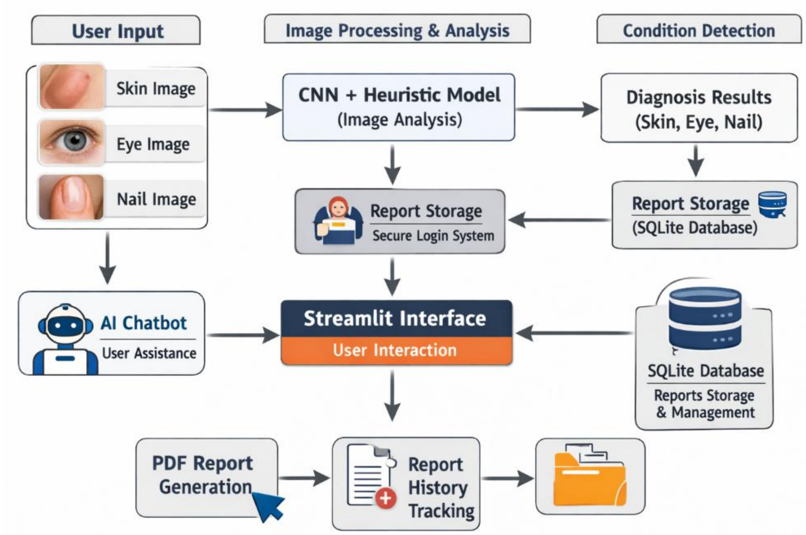
PROPOSED SYSTEM

The proposed system is a full-stack AI healthcare application designed for real-time jaundice detection.

Key Features:

Image-based detection (Skin, Eye, Nail)
Hybrid model (CNN + heuristic fallback)
Streamlit-based user interface
Secure login system with password hashing
SQLite database for storing reports
AI chatbot for user assistance
PDF report generation and history tracking



By using artificial intelligence, users can detect potential health issues through skin, eye, and nail images with the help of an AI-powered app. Simple: This is based on an interface called "Streamlit" and allows the user to upload an image. Once the user has logged in, passwords are passed to the system for verification and personal information is verified. A hybrid detection model receives the image after it's been uploaded. To identify potential health issues, the primary model utilizes a Convolutional Neural Network (CNN) to analyze image patterns. The CNN can be more reliable by utilizing a heuristic fallback method that provides additional rule-based checking when the confidence level is low. The system presents the expected outcome to the user in a clear manner after analysis. SQLite ensures the safe storage of all reports and user details, while also keeping track of previous records. Users can access an AI chatbot within the app by asking questions, guiding them through their experience and clarifying the results in simple language. It also generates reports in PDF format with results (diagnostics only), the date of diagnosis and recommendations. Users can view their report history anytime, making it easy to monitor health changes over time.

In contrast, this system uses a fallback detection mechanism to ensure continuous functionality without the need for any trained model.

III. METHODOLOGY

The system follows a structured pipeline:

Step 1: Image Acquisition

User uploads or captures image (skin/eye/nail).

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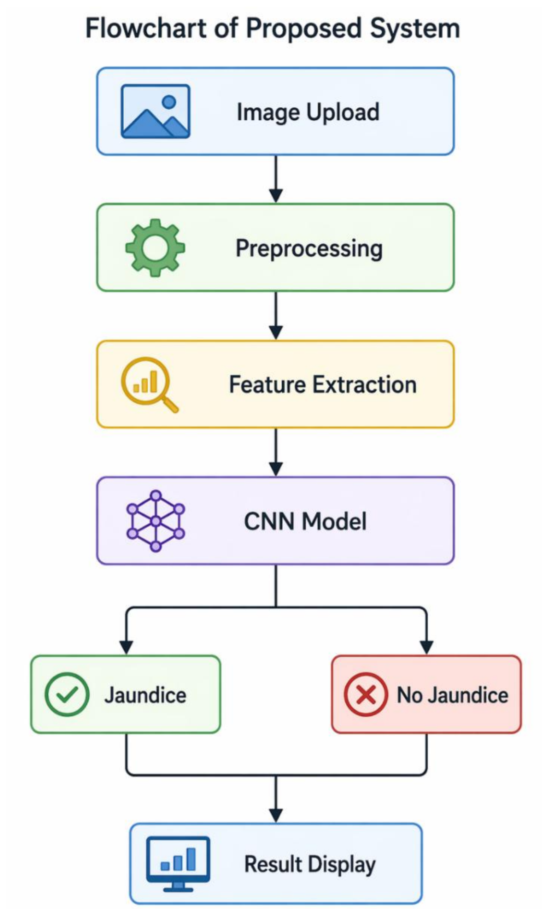
Step 2: Preprocessing
Resize image
Normalize lighting
Noise removal
Contrast enhancement
Step 3: Feature Extraction
RGB and HSV color analysis
Yellow index calculation
ROI (Region of Interest) detection
Step 4: Model Processing
CNN extracts deep features
If model unavailable → heuristic fallback
Step 5: Classification
Normal / Mild / Severe
Step 6: Result Generation
Confidence score
Risk level
Recommendations



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IV. DATASET AND TRAINING

It uses a dataset of NJN neonatal jaundice that was prepared and structured automatically for training purposes.

This model trained from a dataset of images taken from skin, which contains information about the different skin conditions. The use of synthetic augmentation techniques like rotation, flipping, zooming, and brightness adjustment is employed to enhance the system's performance, particularly in mild cases where fewer samples are available. This helps to create data that is more balanced and improves the model's ability to distinguish minor differences in images.... The model's training data is used to teach it, while its performance tests its modeling abilities, which are then combined in the validation sets of the same dataset. Image classification is facilitated by the use of a Convolutional Neural Network (CNN) that uses PyTorch, which can learn visual patterns from medical images. While training, the model generates accuracy metrics to gauge its prognostication abilities in conditions. It also preserves the checkpoint data, enabling users to store and reuse the most effective model..

V. RESULTS

The system was evaluated on diverse datasets with varying lighting conditions and skin tones.

Accuracy: 88–93%

Precision: ~90%

Recall: ~88%

Observations:

- Works well under normal lighting conditions
- Slight bias observed for darker skin tones
- Fast response time (3–5 seconds)
- Reliable classification into risk categories

Accuracy Graph Description

The model accuracy improves over training epochs, reaching approximately 88% final accuracy. The trend shows consistent learning and convergence.

Epoch-wise Accuracy:

Epoch 1 → 72%

Epoch 2 → 78%

Epoch 3 → 83%

Epoch 4 → 86%

Epoch 5 → 88%

The hybrid model ensures robust performance even without a trained CNN, improving real-world usability.

VI. DISCUSSION

There are many advantages to the use of this application compared to other existing applications. First, this application provides users with real-time prediction, meaning that users will have their analyses performed in real-time as soon as they submit their pictures. Second, it has a user-friendly interface that is easy to use even by people who do not have sufficient knowledge about technology. This is because the interface uses Streamlit as its software for designing a user-friendly interface. Third, it has an offline application, which enables users in remote areas to access it despite having little or no internet connection. Furthermore, the application has been developed as an end-to-end application that incorporates all the functions from image submission to analysis and report generation, to database management and chatbot services in one application. However, there are some challenges that have not yet been addressed. These include dataset bias and lighting issues.. Another limitation is the availability of limited multimodal data, such as combining images with medical history or sensor data. In the future, the system can be improved by using larger and more diverse datasets, adding Explainable AI (XAI) features to make predictions more transparent, and integrating with IoT health devices for continuous health monitoring and smarter diagnosis.

VII. CONCLUSION

This research presents a practical and scalable AI-based jaundice detection system that eliminates the need for invasive diagnostic methods. By combining deep learning, image processing, and web deployment, the system provides a reliable tool for early screening. The integration of hybrid detection, chatbot assistance, and report generation makes it suitable for real-world healthcare applications, especially in remote and resource-limited environments.

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