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AI-Based Multi-Modal Disease Screening Using Image Analysis and Rapid Diagnostic Test Recognition

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Abstract: *Early detection of diseases remains a major challenge due to limited access to healthcare facilities and high diagnostic costs, especially in rural and underdeveloped regions. This paper presents an AI-based multi-modal disease screening system that integrates image analysis and Rapid Diagnostic Test (RDT) recognition to provide a non-invasive and cost-effective solution for preliminary health assessment. The system utilizes images of nails, eyes, and facial features along with RDT strip images to identify potential health conditions. Advanced image processing techniques are applied for preprocessing, followed by feature extraction using Convolutional Neural Networks (CNN). Classification is performed using machine learning models such as Support Vector Machine (SVM) and Random Forest.*

The system provides a user-friendly interface and generates color-coded results indicating the health condition of the user. Additionally, a structured PDF report is generated to assist both patients and medical professionals. The proposed solution aims to reduce dependency on laboratory testing and promote preventive healthcare. The system is portable, affordable, and suitable for both rural and urban environments..

Keywords*:* Artificial Intelligence, Multi-Modal Screening, Image Processing, RDT Recognition, Machine Learning, Preventive Healthcare

I. INTRODUCTION

Healthcare accessibility is a major concern in many parts of the world, particularly in rural and remote regions where access to medical infrastructure is limited. Early diagnosis of diseases plays a crucial role in reducing mortality rates and improving overall health outcomes. However, traditional diagnostic methods often require laboratory tests, specialized equipment, and trained professionals, making them expensive and time-consuming.

With the advancement of Artificial Intelligence (AI) and Machine Learning (ML), there has been significant progress in the development of intelligent healthcare systems. Image-based analysis has become a powerful tool for detecting diseases using visible indicators such as skin color, eye condition, and nail texture. Similarly, Rapid Diagnostic Tests (RDTs) are widely used for detecting diseases such as malaria and dengue, but manual interpretation can lead to errors.

The proposed system introduces a multi-modal approach that combines image analysis and RDT recognition to provide a comprehensive screening solution. By analyzing multiple inputs, the system improves accuracy and reliability. The system is designed to be low-cost, portable, and easy to use, making it suitable for deployment in both rural and urban areas.

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II. SYSTEM COMPONENTS

The proposed system consists of multiple modules that work together to perform disease screening.

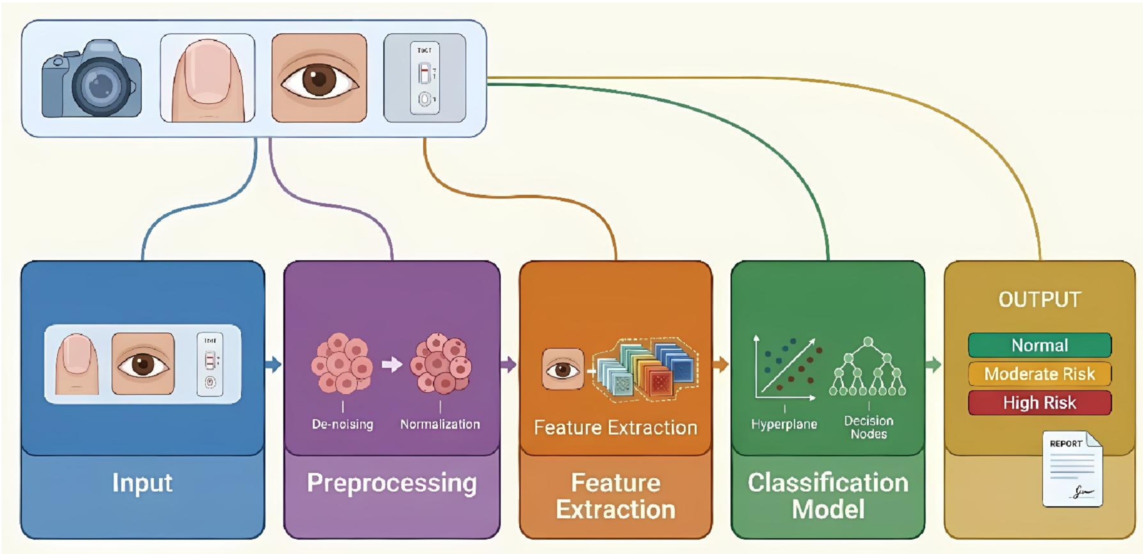

Fig. 1 Flow Diagram of Proposed Multi-Modal Disease Screening System

A. Input Module

The input module is responsible for acquiring all necessary data required for disease screening. It captures images of nails, eyes, facial features, and Rapid Diagnostic Test (RDT) strips using a smartphone or camera device. These images act as the primary source of information for analysis. Proper image capture under good lighting conditions is important to ensure accuracy in further processing. The module supports multiple input types, making the system flexible and capable of detecting a wide range of diseases.

B. Preprocessing Module

The preprocessing module prepares the captured images for further analysis by improving their quality and consistency. It performs operations such as resizing, normalization, noise removal, and contrast enhancement. These techniques help in eliminating unwanted distortions and variations caused by lighting or camera quality. Proper preprocessing ensures that the important features are preserved while irrelevant information is removed, thereby improving the efficiency and accuracy of the machine learning models used in later stages.

C. Feature Extraction Module

The feature extraction module plays a crucial role in identifying important patterns from the input images. It uses Convolutional Neural Networks (CNN) to automatically extract relevant features such as color variations, textures, and shapes. These features are essential for detecting abnormalities associated with different diseases. The use of deep learning techniques reduces the need for manual feature selection and improves the overall performance of the system by capturing complex patterns from the data.

D. Classification Module

The classification module is responsible for analyzing the extracted features and predicting the health condition of the user. It uses machine learning algorithms such as Support Vector Machine (SVM) and Random Forest to classify the data into different categories. Based on the trained model, the system determines whether the condition is normal or indicates a potential health risk. The use of multiple classifiers improves the reliability and accuracy of predictions.

E. Output Module

The output module presents the final results to the user in an easy-to-understand format. It displays color-coded results indicating Normal, Moderate Risk, or High-Risk conditions. In addition to visual output, the system generates a

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detailed PDF report containing the analysis results, which can be used for medical consultation. This module enhances usability by providing clear and structured information for both users and healthcare professionals.

III. SOFTWARE & TECHNOLOGIES USED

The proposed system is developed using a combination of programming tools, machine learning frameworks, and image processing libraries. These technologies work together to enable efficient data processing, feature extraction, classification, and user interaction. The selection of these tools ensures flexibility, scalability, and accurate performance of the system.

A. Python Programming Language

Python is used as the primary programming language for developing the system due to its simplicity, readability, and extensive support for scientific computing and artificial intelligence applications. It provides a large number of libraries that simplify tasks such as image processing, machine learning, and data handling. Python enables rapid development and easy integration of different modules, making it an ideal choice for building AI-based healthcare systems.

B. OpenCV (Open Source Computer Vision Library)

OpenCV is an open-source computer vision library used for performing various image processing operations. It is responsible for tasks such as image resizing, color space conversion, filtering, noise reduction, and edge detection. OpenCV helps in improving the quality of input images before they are passed to machine learning models. It also plays a key role in detecting patterns in RDT strips and enhancing features required for accurate analysis.

C. TensorFlow / Keras

TensorFlow and Keras are powerful deep learning frameworks used to implement Convolutional Neural Networks (CNN) in the system. These frameworks allow the model to automatically learn features from input images without manual intervention. CNNs are particularly effective in identifying patterns such as color variations, textures, and shapes that are associated with different diseases. Keras provides a user-friendly interface for building and training models, while TensorFlow ensures efficient computation and scalability.

D. Scikit-learn

Scikit-learn is a widely used machine learning library that provides tools for data analysis and model development. In this system, it is used to implement classification algorithms such as Support Vector Machine (SVM) and Random Forest. These algorithms analyze the features extracted by the CNN model and classify them into different health conditions. Scikit-learn also provides functionalities for model evaluation and performance optimization.

E. GUI Framework (Tkinter / Custom UI)

A graphical user interface (GUI) is developed using Tkinter or similar frameworks to provide an interactive platform for users. The GUI allows users to upload images, view results, and generate reports in a simple and efficient manner. It improves the usability of the system and ensures that even non-technical users can operate the application easily.

F. PDF Report Generation Tools

The system includes a report generation module that creates detailed PDF reports based on the analysis results. These reports include information about the detected condition, risk level, and suggested actions. The PDF reports can be stored for future reference or shared with healthcare professionals for further diagnosis. This feature enhances the practical usability of the system.

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IV. BLOCK DIAGRAM

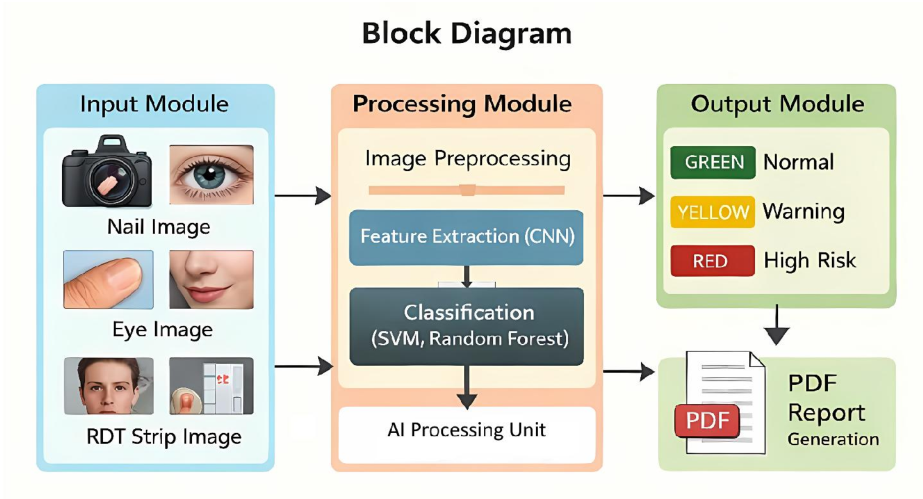

Fig. 2 Block Diagram of Proposed System

V. SYSTEM ARCHITECTURE

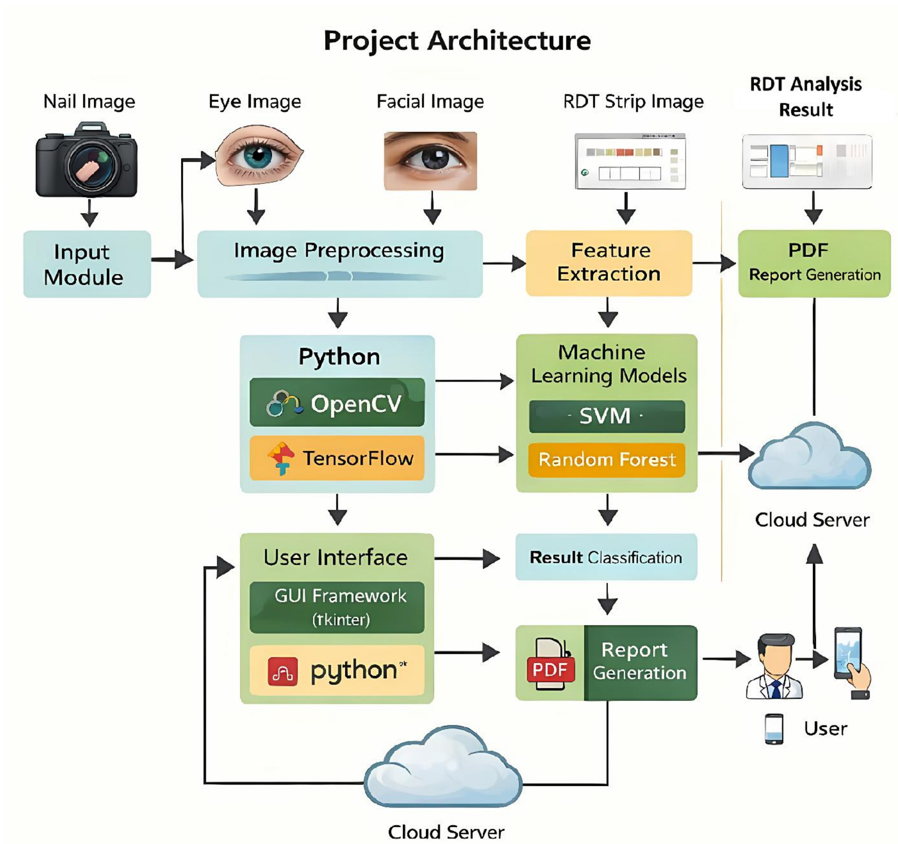

Fig. 3 System Architecture of AI-Based Multi-Modal Disease Screening System

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VI. WORKING

The working of the proposed AI-based multi-modal disease screening system begins with the acquisition of input data through a smartphone or camera device. The user captures images of nails, eyes, facial features, or Rapid Diagnostic Test (RDT) strips. These images act as the primary input for the system and must be captured under proper lighting conditions to ensure better accuracy.

Once the images are acquired, they are passed to the preprocessing module. In this stage, various image enhancement techniques such as resizing, normalization, noise removal, and contrast adjustment are applied. These operations help in improving image quality and removing unwanted distortions, ensuring that the important features are preserved for further analysis.

After preprocessing, the system performs feature extraction using Convolutional Neural Networks (CNN). The CNN model automatically learns and extracts significant features such as color variations, texture patterns, edges, and shapes from the input images. These features are crucial for identifying abnormalities related to diseases like anemia, jaundice, and infections detected through RDT strips.

The extracted features are then fed into machine learning models such as Support Vector Machine (SVM) and Random Forest. These models analyze the data and classify it into different categories based on trained patterns. The classification stage determines whether the detected condition is normal or indicates a potential health risk.

Finally, the output module presents the results in a user-friendly manner using a color-coded system (Green for Normal, Yellow for Moderate Risk, and Red for High Risk). In addition to displaying results, the system generates a detailed PDF report containing the analysis summary, which can be used for medical consultation and future reference. This complete workflow ensures accurate, fast, and efficient disease screening.

VII. ADVANTAGES

- Provides a non-invasive and user-friendly method for disease screening without requiring blood samples
- Offers a low-cost solution that can be easily deployed in rural and resource-limited areas
- Enables multi-modal disease detection using different input sources such as nails, eyes, facial images, and RDT strips
- Reduces dependency on laboratory testing and minimizes waiting time for results
- Provides quick and efficient analysis using AI and machine learning techniques
- Generates automated PDF reports, improving documentation and record keeping
- Can be used by both medical professionals and non-technical users due to its simple interface
- Enhances early detection of diseases, leading to timely medical intervention
- Portable and scalable system that can be deployed on laptops or mobile devices
- Reduces human error in interpreting diagnostic results such as RDT strips

VIII. APPLICATIONS

- Used in rural healthcare centers where access to advanced diagnostic facilities is limited
- Supports telemedicine by allowing remote disease screening and consultation
- Useful in medical camps and awareness programs conducted by NGOs and government organizations
- Can be used for personal health monitoring and early detection of potential diseases
- Applicable in hospitals and clinics as a preliminary screening tool before detailed diagnosis
- Helpful in educational institutions for demonstrating AI-based healthcare systems
- Can assist healthcare workers in making faster decisions during emergencies
- Suitable for integration into mobile applications for widespread accessibility
- Can be deployed in community health programs for large-scale screening

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