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Heart Disease Prediction Using Retinal Images with Deep Learning

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***Abstract*—Heart disease is one of the major causes of mortality worldwide, and its early detection is essential for saving lives. This project focuses on developing a non-invasive system for heart disease prediction using retinal images. The retinal scans are processed and analyzed with the help of Python programming language using libraries such as NumPy, Pandas, and OpenCV for preprocessing and feature handling. The core implementation is carried out using deep learning models, particularly Convo-lutional Neural Networks (CNNs), built with TensorFlow/Keras or PyTorch, which help in extracting vascular patterns and detecting hidden indicators of heart disease. For evaluating per-formance, statistical measures and visualizations are generated. By integrating these tools and techniques, the project provides a cost-effective and accessible diagnostic aid that assists healthcare professionals in identifying risks at an early stage, reducing the need for invasive procedures and enabling better preventive care. *Index Terms*—Heart disease prediction, retinal imaging, deep learning, convolutional neural networks (CNN), medical image processing, non-invasive diagnosis, feature extraction, healthcare analytics.**

I. Introduction

Heart disease continues to be one of the leading causes of mortality worldwide, posing a significant challenge to global healthcare systems. According to recent studies, a large number of deaths occur due to late diagnosis and lack of timely medical intervention. Early detection of cardiovascular diseases plays a crucial role in reducing mortality rates and improving patient outcomes. However, conventional diagnostic techniques such as electrocardiography (ECG), angiography, echocardiography, and blood tests are often invasive, expen-sive, and require specialized medical infrastructure. These limitations make them less accessible, particularly in rural and underdeveloped regions, where healthcare resources and trained professionals are limited.

To overcome these challenges, there is a growing need for non-invasive, cost-effective, and easily accessible diagnostic solutions. One promising approach involves the use of retinal fundus imaging. The human retina provides a unique and direct view of the body's microvascular system. Since the retinal blood vessels share similar anatomical and physio-logical properties with coronary blood vessels, changes in retinal vasculature—such as narrowing, dilation, tortuosity, and branching abnormalities—can serve as important indica-tors of cardiovascular diseases. Therefore, analyzing retinal images offers a reliable and non-invasive method for early heart disease prediction.

In this project, titled "Heart Disease Prediction Using Retinal Images," a computational framework is developed to analyze retinal fundus images and predict the presence of heart disease. The system utilizes image processing techniques for preprocessing, including resizing images to a standard dimension (224 × 224 pixels), normalization, noise removal, and enhancement to improve image quality. These processed images are then provided as input to a deep learning model.

A Convolutional Neural Network (CNN), specifically a transfer learning-based ResNet-18 architecture, is employed for feature extraction and classification. The model automat-ically learns complex vascular patterns from retinal images and identifies hidden features associated with heart disease. Transfer learning enables the model to achieve higher accuracy even with limited datasets by leveraging pre-trained weights and adapting them to the current classification task.

The system is designed with a user-friendly interface that allows users to upload retinal images through a web application. Once the image is uploaded, it undergoes preprocessing and is passed through the trained model, which predicts whether heart disease is present or not. The output is displayed along with a confidence score, providing users with an interpretable and reliable result. The backend processing is implemented using Python and deep learning frameworks such as PyTorch, along with libraries like NumPy, Pandas, OpenCV, and PIL for efficient data handling and image processing .

The proposed system offers several advantages over traditional methods. It is completely non-invasive, cost-effective, and capable of providing rapid predictions, making it suitable for large-scale screening and remote healthcare applications. Additionally, it can be integrated into telemedicine platforms, enabling healthcare professionals to monitor patients in real time and make informed decisions. By reducing dependency on expensive diagnostic procedures and improving accessibility, especially in rural areas, the system contributes to early detection and preventive healthcare.

In summary, this work demonstrates the potential of retinal image analysis combined with deep learning techniques as an effective tool for heart disease prediction. It provides a scalable, efficient, and accessible solution that can assist medical practitioners in early diagnosis and ultimately help reduce the global burden of cardiovascular diseases.

II. Literature Survey

A. Related Work

Recent advancements in deep learning and medical image analysis have enabled significant progress in non-invasive cardiovascular disease prediction using retinal images.

In [1], the authors proposed a deep learning-based framework to predict cardiovascular outcomes in individuals with type 2 diabetes using routine retinal fundus images. The study utilized a dataset of over 6,000 patients and applied the EfficientNet-B2 architecture with transfer learning. Preprocessing techniques such as contrast enhancement (CLAHE), normalization, and background removal were employed to improve feature extraction. The model achieved an AUC score of 0.697, which is comparable to traditional clinical risk scores. Additionally, Grad-CAM visualization demonstrated that regions such as the optic disc and blood vessels play a crucial role in prediction. The study also highlighted the potential of longitudinal retinal analysis for continuous risk monitoring.

In [2], the authors introduced a deep learning model named Reti-WHO, which focuses on improving the stability of cardiovascular disease risk prediction using retinal images. A large longitudinal dataset containing over 55,000 images collected over six years was used. Unlike traditional CNNs, the study employed a Swin Transformer architecture, which captures complex spatial relationships in retinal images. The model demonstrated strong performance with a correlation coefficient of 0.710 and high sensitivity for identifying high-risk patients. A key contribution of this work is the improved stability of predictions over time, addressing fluctuations seen in traditional WHO risk scores. The study also confirmed that retinal vascular features such as tortuosity and vessel caliber are strong indicators of cardiovascular risk.

In [3], a deep learning-based multimodal framework was proposed for heart disease risk prediction by combining retinal images with clinical data. The model used EfficientNet-B3 for feature extraction and integrated structured health parameters such as blood pressure, cholesterol, and BMI through a feature fusion mechanism. Extensive preprocessing techniques, including normalization, augmentation, and histogram equalization, were applied to improve model robustness. The proposed system achieved high performance with an accuracy of 92.4

Overall, these studies demonstrate that retinal fundus imaging combined with deep learning techniques provides an effective, non-invasive approach for cardiovascular risk prediction. Advanced architectures such as EfficientNet and Transformers, along with feature visualization techniques, have significantly improved prediction accuracy and reliability.

B. Research Gap

Despite significant progress in retinal image-based cardiovascular disease prediction, several important limitations remain in existing approaches.

First, many existing studies focus primarily on model accuracy and advanced architectures such as EfficientNet and Transformers, but they often overlook the development of a complete end-to-end system that includes data preprocessing, prediction, and user interaction. In real-world healthcare applications, especially in rural and resource-limited areas, a fully integrated system is essential for practical usability.

Second, most research works rely on large-scale datasets and complex models, which require high computational resources for training and deployment. This limits their applicability in low-cost environments where hardware resources such as GPUs are not readily available. There is a need for lightweight and efficient models, such as ResNet-18, that can provide high accuracy with reduced computational complexity.

Third, existing solutions often lack user-friendly interfaces for real-time prediction. Many models are confined to experimental or clinical research settings and do not provide accessible platforms where users or healthcare workers can easily upload retinal images and obtain instant results.

Fourth, although some studies explore multimodal approaches by combining retinal images with clinical data, such systems increase data dependency and complexity, making them less practical for quick screening. A system that relies only on retinal images as input is more suitable for rapid, non-invasive, and scalable screening.

Fifth, traditional diagnostic systems are still widely used despite being invasive, time-consuming, and expensive, and there is a gap in replacing or supporting these methods with automated, non-invasive, and cost-effective solutions.

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Finally, there is limited focus on deployment and real-time application, such as web-based platforms for prediction and visualization. Integrating deep learning models with frameworks like Streamlit for real-time interaction is still an emerging area.

To address these gaps, the proposed system develops a non-invasive, efficient, and deployable heart disease prediction model using retinal images, supported by:

Efficient preprocessing techniques A lightweight CNN model (ResNet-18) A web-based interface for real-time prediction High accuracy with reduced computational requirements

This makes the system practical, scalable, and suitable for real-world healthcare applications, particularly in rural and resource-constrained environments.

III. PROPOSED METHODOLOGY

The proposed system for heart disease prediction using retinal images follows a structured and systematic methodology to ensure accurate, efficient, and reliable results. The system utilizes retinal fundus images as the primary input and processes them through multiple stages, including data collection, preprocessing, model development, and output generation.

Initially, retinal images are collected from publicly available datasets such as Kaggle and IEEE repositories. These datasets consist of labeled images categorized into heart disease and no heart disease classes, enabling supervised learning. The diversity of the dataset improves the model's ability to generalize and perform well on unseen data.

Before feeding the images into the model, preprocessing techniques are applied to enhance image quality and ensure uniformity. All images are resized to a standard dimension of 224 × 224 pixels to match the input requirements of the model. Pixel values are normalized to improve convergence during training, and noise removal and enhancement techniques are applied to highlight important retinal features, particularly blood vessels. The processed images are then converted into tensor format for compatibility with deep learning frameworks.

The core of the system is a Convolutional Neural Network (CNN) based on the ResNet-18 architecture. This model is selected due to its efficiency and ability to handle deep networks using residual connections, which help overcome vanishing gradient problems. The model automatically extracts relevant features from retinal images and learns complex patterns associated with cardiovascular diseases. During training, the model optimizes its parameters to achieve high classification accuracy.

The system workflow begins with the user uploading a retinal image through the web interface. The image undergoes preprocessing and is then passed to the trained CNN model for prediction. The model analyzes the extracted features and classifies the image into either heart disease or no heart disease.

The output is generated through an interactive Streamlit-based interface. The system displays the prediction result along with a confidence score, which represents the probability of the predicted class and is computed using the Softmax function. Additionally, the system supports PDF report generation,

Fig. 1. System Architecture

which includes patient details, prediction results, confidence scores, and basic health suggestions. This structured output ensures easy interpretation and assists both users and healthcare professionals in making informed decisions.

A. System Architecture

The proposed system follows a sequential pipeline integrating user input, image processing, deep learning, and result generation. The user first enters patient details, which are validated to ensure correctness. A retinal fundus image is then uploaded through the web interface.

The uploaded image undergoes preprocessing, including resizing to 224 × 224 pixels, normalization, and conversion into tensor format. The processed image is passed to a ResNet-18 based CNN model, which extracts vascular features and predicts the presence of heart disease.

The system outputs the prediction (Heart Disease or No Heart Disease) along with a confidence score calculated using the Softmax function. Based on the result, health suggestions are provided. Additionally, a PDF report containing patient details, prediction, and recommendations is generated and made available for download.

Overall, the system provides a non-invasive, efficient, and user-friendly solution for heart disease prediction.

IV. IMPLEMENTATION

A. Tools and Technologies Used

1) Hardware Requirements:

- Processor: Intel Core i5 (Recommended: i7 or higher)
- RAM: Minimum 8 GB
- Graphics: 2 GB GPU (e.g., NVIDIA GTX 1050 or higher, optional)
- Storage: 500 GB (for datasets and models)
- Internet: Stable connection (for deployment and updates)

2) Software Requirements:

- Operating System: Windows / Ubuntu / macOS
- Programming Language: Python (3.8 or higher)
- Framework: Streamlit
- Backend: Python (Streamlit + PyTorch)
- Designing: Streamlit UI with Custom CSS
- Libraries: PyTorch, OpenCV, PIL, NumPy, Pandas, Scikit-learn
- IDE/Editor: VS Code / PyCharm
- Version Control: Git
- Database: Not applicable (no persistent storage)

Fig. 2. web interface for entering patient details

Fig. 3. Image upload

3) Technologies Used:

- Deep Learning: CNN (ResNet-18) implemented using PyTorch for feature extraction and classification
- Image Processing: OpenCV and PIL for preprocessing (resizing, normalization, enhancement)
- Web Application: Streamlit for image upload and prediction interface
- Model Deployment: Direct deployment within Streamlit for real-time prediction
- User Interface: Streamlit components with custom CSS
- Data Handling: Temporary processing without database storage
- Report Generation: FPDF for generating downloadable reports

B. System Modules

The proposed system consists of multiple modules that work together to provide efficient heart disease prediction.

Image Upload Module: Allows users to upload retinal images (JPG, JPEG, PNG) and validates the input. Preprocessing Module: Performs image resizing (224 × 224), normalization, and conversion to tensor format to prepare data for the model. Prediction Module: Uses a ResNet-18 CNN model to analyze the image and generate a prediction along with a confidence score. User Interface Module: Developed using Streamlit, it provides input forms, image upload functionality, and prediction controls with enhanced UI using CSS. Result Display Module: Displays the prediction (Heart Disease / No Heart Disease) along with confidence percentage in a clear format. Report Generation Module: Generates a downloadable PDF report containing patient details, prediction results, and health suggestions.

V. Results and Discussion

A. Output Examples

The system provides a user-friendly interface for entering patient details such as name, age, gender, phone number, and email.

Users can upload retinal fundus images through the interface, supporting formats like JPG, JPEG, and PNG.

The uploaded image is displayed for verification before prediction.

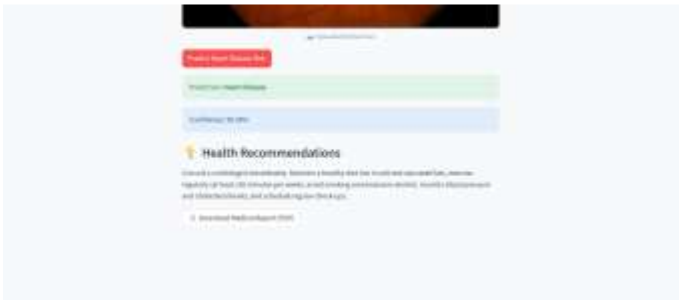
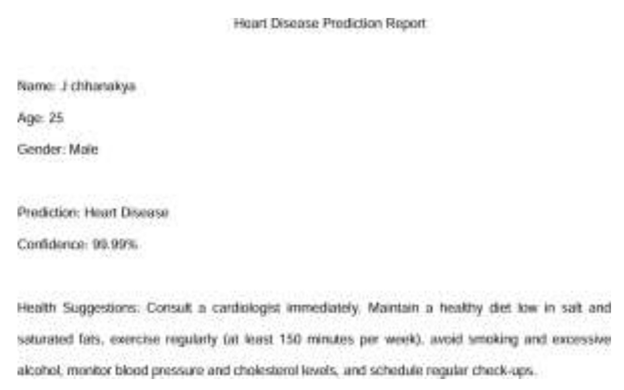


Fig. 4. Prdiction results

The system performs prediction using the trained model and displays the result as: Heart Disease or No Heart Disease A confidence score (e.g., 99.99The system also provides health recommendations based on the prediction outcome. A PDF report is generated containing patient details, prediction results, confidence score, and health suggestions. The final output allows users to view and download the report, ensuring easy access and record-keeping.

B. Performance Metrics

- **Accuracy:** 97.06%



Heart Disease Prediction Report

Name: J chhanakya

Age: 25

Gender: Male

Prediction: Heart Disease

Confidence: 99.99%

Health Suggestions: Consult a cardiologist immediately. Maintain a healthy diet low in salt and saturated fats, exercise regularly (at least 150 minutes per week), avoid smoking and excessive alcohol, monitor blood pressure and cholesterol levels, and schedule regular check-ups.

Fig. 5. Pdf report

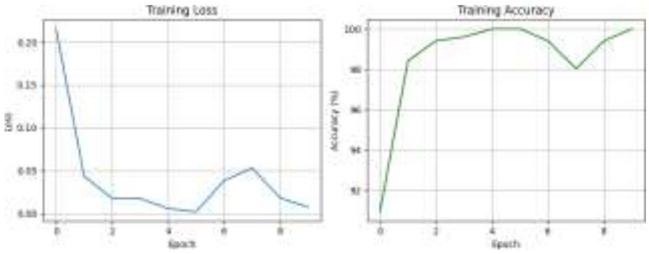


Fig. 6. Training Loss & Training Accuracy

- **Precision:** 100%
- **Recall:** 90%
- **F1 Score:** 94.74%

C. *Training Performance Analysis*

The training graphs illustrate the performance of the proposed ResNet-18 model over multiple epochs.

- Training Loss: The loss decreases significantly from approximately 0.22 to near 0.01 as the number of epochs increases. This indicates that the model is effectively learning and minimizing prediction error. Minor fluctuations in intermediate epochs are observed, but the overall trend shows stable convergence.
- Training Accuracy: The accuracy increases steadily from around 94.5% to nearly 100% across epochs. This demonstrates that the model improves its classification capability as training progresses.
- Observation: The decreasing loss and increasing accuracy confirm that the model is well-trained, stable, and capable of achieving high prediction performance without significant overfitting.

VI. Advantages / Applications

- Non-invasive: The proposed system utilizes retinal fundus images for heart disease prediction, eliminating the need for invasive diagnostic procedures such as angiography or blood tests. This makes the process safe and painless.
- Cost-effective: The system reduces dependency on expensive medical tests and equipment, providing an affordable solution for early diagnosis.
- Useful in Rural Areas: The system can be deployed in rural and remote regions where advanced healthcare facilities are limited, improving accessibility to early detection.
- Early Detection: The model can identify subtle changes in retinal blood vessels, enabling early-stage detection of heart disease risk.
- Fast and Automated: The system provides quick predictions within seconds, reducing diagnosis time and minimizing human effort.
- Support for Healthcare Professionals: It acts as a supportive tool for doctors by providing additional insights for better decision-making.

VII. Conclusion

The proposed system presents a non-invasive approach for heart disease prediction using retinal image analysis and deep learning techniques. A Convolutional Neural Network (CNN) based on the ResNet-18 architecture is used to extract features and classify retinal images into heart disease and non-heart disease categories.

The system integrates preprocessing, model prediction, and a Streamlit-based interface to provide real-time results along with confidence scores. It also generates a PDF report containing patient details, prediction outcomes, and health recommendations.

Experimental results demonstrate high performance in terms of accuracy, precision, recall, and F1-score, confirming the effectiveness of the model. The training performance also shows stable convergence and reliable learning.

Overall, the system provides a fast, cost-effective, and accessible solution for early heart disease detection. It has strong potential for real-world healthcare applications, especially in rural and resource-limited areas. Future work may include using larger datasets, improving model performance, and deploying the system on mobile or cloud platforms.

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