National Journal of Signal and Image Processing, ISSN: 3107-5231 Vol. 1, No. 4, 2025 (pp. 59-66)

RESEARCH ARTICLE

ECEJOURNALS.IN

Hypertension and Heart Attack Detection System Based on Retinal Image Analysis

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KEYWORDS:
Retinal Imaging,
Hypertension Detection,
Cardiovascular Risk,
Microvascular Analysis,
Fundus Photography,
Vascular Abnormalities,
Early Diagnosis.

ARTICLE HISTORY:
Submitted : 09.06.2025
Revised : 05.08.2025
Accepted : 19.09.2025

https://doi.org/10.17051/NJSIP/01.04.09

Abstract

This study tackles the important problem of delayed and erroneous identification of hypertension and heart attack risk, which continue to be major causes of cardiovascular deaths worldwide. Traditional diagnostic approaches, such blood pressure monitoring and electrocardiograms, have limitations. They can be intrusive, unreliable, or not suited for large-scale screening. As a result, many instances go undetected until serious organ damage occurs. The suggested method uses retinal fundus imaging, paired with deep learning, to identify tiny microvascular changes that indicate systemic cardiovascular problems. The main objective is to design a diagnostic method that is non-invasive, inexpensive, and automated. This method should help with early detection in both clinical settings and places with little resources. The proposed system processes retinal pictures using vessel segmentation, feature extraction, and classification with a Convolutional Neural Network (CNN). This produces understandable results, which are then improved by heatmap visualizations. This study is new because it combines training on many retinal datasets, detailed understanding of vascular features, and explainable artificial intelligence. This approach aims to find biomarkers connected to high blood pressure and heart attacks that might not be easily seen by doctors.

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How to cite this article: Zabiyulla SG, Sejina H. Hypertension and Heart Attack Detection System Based on Retinal Image Analysis. National Journal of Signal and Image Processing, Vol. 1, No. 4, 2025 (pp. 59-66).

Introduction

Cardiovascular illnesses remain the leading cause of death globally, with high blood pressure and heart attacks being the most common and avoidable health problems. These disorders generally develop gradually, developing over years without visible symptoms until they lead to serious health problems. A major difficulty in global healthcare is the late or delayed identification of high blood pressure. This condition is sometimes only found after severe damage to the blood vessels has already occurred. Although frequently used, clinical blood pressure measurements only provide a single picture of a person's state, which doesn't fully represent the constant changes in their physiology. Moreover, standard methods for assessing cardiovascular risk, such as electrocardiograms, echocardiograms, and CT scans, are expensive, typically require invasive procedures, and are not practicable for broad, routine screening. As a result, many people stay undiagnosed, particularly in areas with minimal resources where specialized medical facilities are not easily accessible. Therefore, there's a strong demand for approaches that are non-invasive, inexpensive, and scalable. These methods should be able to detect early blood vessel changes related to high blood pressure and the possibility of heart problems.

The human retina offers a distinctive avenue for tackling this problem. The eye is unique because it allows for the direct, non-invasive observation of blood arteries in a living organism. The small blood vessels in the retina are very sensitive to changes in the body's blood vessels. This makes them a useful indicator for spotting early indicators of high blood pressure and heart problems. Several clinical investigations have revealed significant associations between retinal vascular irregularities—including arteriolar constriction, venular widening, arteriovenous nicking, microaneurysms, and hemorrhages—and systemic cardiovascular ailments. These little blood vessel changes act as early signs of physical decline, appearing before any noticeable symptoms. Digital fundus photography has made retinal imaging more accessible, allowing for the quick acquisition of high-quality retinal pictures, even outside of specialist medical institutions.

At the same time, deep learning has become a major force in medical picture analysis. Convolutional Neural Networks (CNNs) have shown a strong capacity to automatically extract complicated visual elements. This makes them well-suited for assessing the intricate structures found in retinal pictures. Unlike physical inspection, which is subjective and strongly dependent on an expert's knowledge, CNN-based models may uncover subtle patterns and early microvascular alterations that are typically unseen to the human eye. This capacity is especially important for identifying early signs of high blood pressure that indicate a higher risk of heart problems. Using vascular segmentation, feature extraction, and classification, Convolutional Neural Networks (CNNs) may learn certain shape characteristics linked to high blood pressure and heart problems. This allows them to make consistent and objective diagnostic predictions.

Therefore, using deep learning with retinal imaging offers a potent way to identify cardiovascular risk early on. The goal of this project is to create an intelligent system that can analyze retinal images. This system will segment the blood vessels, identify important biomarkers, classify the images into diagnostic categories, and create visual maps that highlight the areas used for prediction. The system's architecture, which uses recognized medical imaging datasets and strong preprocessing methods, aims to provide dependable performance across various imaging situations. The ultimate goal of this strategy is to support healthcare professionals, improve community screening programs, and give an easy way to identify high blood pressure and the risk of heart attacks early on. This, in turn, would help reduce deaths from heart disease worldwide..

This work is structured with the literature survey review given in Section II. Section III outlines the methodology, with specific focus on its operationality. Results and discussions are in Section IV. Finally, Section V ends with the ultimate findings and recommendations.

Literature Survey

The recent work in retinal image analysis has expanded significantly, with rising evidence that microvascular patterns are related to overall cardiovascular health. Recent studies increasingly focus on using deep learning methods to identify hypertension and cardiovascular risks by analyzing fundus pictures. Previous studies have highlighted the importance of how blood vessels are structured, the process of identifying features, and the use of automated screening methods. This work provides a foundation for developing more accurate and therapeutically useful diagnostic tools.

This study investigates retinal pictures to improve the consistent evaluation of cardiovascular risk across different camera systems. The focus is on identifying significant danger signals and maintaining[7] consistency across different imaging areas. The results show a consistent risk alignment, which justifies the use of portable screening methods. This research highlights the potential of retinal imaging to provide early insights into cardiovascular health. This expands the possibilities for preventive assessments in many clinical settings, which could improve community health. This study focuses on identifying cardiovascular risk by observing changes in the retinal blood vessels, which are connected to high blood pressure and heart problems. The study shows unusual features in the veins, which indicate stress in the blood vessels. The goal[8] is to identify early warning signs by carefully examining the retina and related visual cues. This study stresses the necessity of accessible screening for younger people and the need to increase knowledge of cardiovascular health patterns.

This study analyzes how stress on blood vessels affects the risk of heart attacks, as seen in the eye's blood vessels. The study shows modest visual signs that could appear before any clinical symptoms. By evaluating [9] the features of the vessels, this method hopes to help quickly identify dangerous tendencies. The findings underscore the need of early detection, especially among younger populations, and further validate the utility of retinal imaging in both preventative cardiovascular evaluation and the promotion of public health understanding. This work highlights the potential of combining retinal traits with cardiovascular signals to improve how we assess overall risk. This approach underlines the need of combining visual biomarkers[10] with physiological patterns to better understand individual health differences. The results reveal enhanced dependability and easier understanding, which offers a practical way to use preventive screening. This method offers a way to evaluate cardiovascular risk that is scalable, efficient, and therapeutically useful.

This study provides a method for early detection of cardiovascular risk, based on analyzing important patterns seen in retinal images. The focus is on understanding both the specific structures[11] and the larger environmental factors associated to blood vessel health. The study shows the improved clarity of assessments, which is achieved through a full knowledge of visual information. The results demonstrate improved accuracy and efficiency, highlighting the framework's value in enabling early interventions and achieving better long-term cardiovascular health. This study presents a non-invasive method for assessing cardiovascular health by categorizing retinal pictures into general risk groups. The relevance of combining visual data with clinical context[12] to improve decision-making is emphasized. The results indicate better reliability when both perspectives are included. The study's results encourage the use of retinal examinations as accessible tools for early cardiovascular assessment and universal preventive healthcare.

This work presents a system that uses retinal observations and medical information to assess cardiovascular risk. These factors show connections between lifestyle, biological characteristics, and blood vessel health. This method emphasizes clearer[13] interpretations to assist clinical application. The results suggest excellent predictive power, emphasizing the usefulness of combining ocular and contextual information for early identification and tailored cardiovascular care.

This study studies how changes in the small blood vessels of the retina are related to heart and blood vessel diseases, and how these changes are connected to overall health. The initial signs of possible problems[14] are shown by the constriction, twisting, and widening of blood vessels. By understanding these visual patterns, the study attempts to uncover potential dangers before they develop into serious problems. This study highlights the need of examining the retina to encourage early cardiovascular awareness and preventive actions. This study demonstrates how retinal imaging can be used to assess cardiovascular health early on, by identifying small problems in blood vessels that are associated to big health issues. The necessity[15] for quick detection to avoid major occurrences is a global concern. This study demonstrates the potential of retinal observations as useful tools for preventive health management. By understanding visual cues that reflect systemic disorders, the research supports improved health outcomes and lower long-term risks.

This study stresses a basic method for identifying cardiovascular risks by examining the retina for visual indications. This method exposes unusual features in blood vessels, which could[16] indicate underlying health problems. Designed for ease of use, the system provides healthcare professionals with rapid assessments, all inside a straightforward interface. The consistent accuracy of retinal imaging strengthens its value in clinical settings for early detection of cardiovascular risk. This study aims to understand how the tiny blood vessels in the body relate to larger cardiovascular risks, particularly those linked to high blood pressure and heart problems. Recognizing unusual patterns[17] in retinal blood vessels is crucial for identifying concealed health problems. This study shows how early visual signs might help drive preventative health measures. The results support the idea that retinal imaging is a useful technique for assessing cardiovascular health in a preventive way.

This study evaluates electronic health records to determine the likelihood of chronic renal disease and coronary artery disease in people with metabolic disorders. The study shows important demographic[18] and diagnostic characteristics that determine long-term health outcomes. The study hopes to help identify major dangers sooner by analyzing these trends. The findings underscore the significance of informed monitoring for better patient guidance and enhanced decision-making.

This study addresses the use of visual cardiovascular indicators found in retinal images to improve the accuracy of risk assessments. Recognizing[19]] early warning signs is crucial for preventing serious problems. The results demonstrate that a more detailed knowledge of visual information is helpful for quickly assessing health. This study supports the idea that retinal imaging is a useful, non-invasive method for healthcare professionals to use in enhancing cardiovascular health. This study analyzes different methods for finding important retinal features that are related to systemic disorders. The increasing occurrence of disorders that affect both the retina and the cardiovascular system[20] is highlighted. The talk emphasizes how structured visual analysis might reduce differences in diagnoses and lessen the burden on healthcare professionals. The survey's results underline the necessity of reliable retinal surveillance for early detection and better health management.

Methodology

The technique offers a systematic technological process. This process is aimed to translate raw retinal fundus images into accurate diagnostic predictions, specifically for assessing the risk of hypertension and heart attacks. This system brings together dataset collecting, preprocessing, augmentation, and the creation of deep-learning models, all inside a single, streamlined workflow. Each stage is designed to ensure the input data is standardized, clinically relevant, and optimally prepared for feature extraction by the Convolutional

Neural Network. By using vessel segmentation, contrast enhancement, and normalization, we can preserve important characteristics about the microvasculature. At the same time, augmentation and class-balancing methods help to make the model more reliable. These combined methods generate a reliable, scalable, and clinically useful system. This approach can identify tiny retinal anomalies that are related to problems with the cardiovascular system as shown in figure 1.

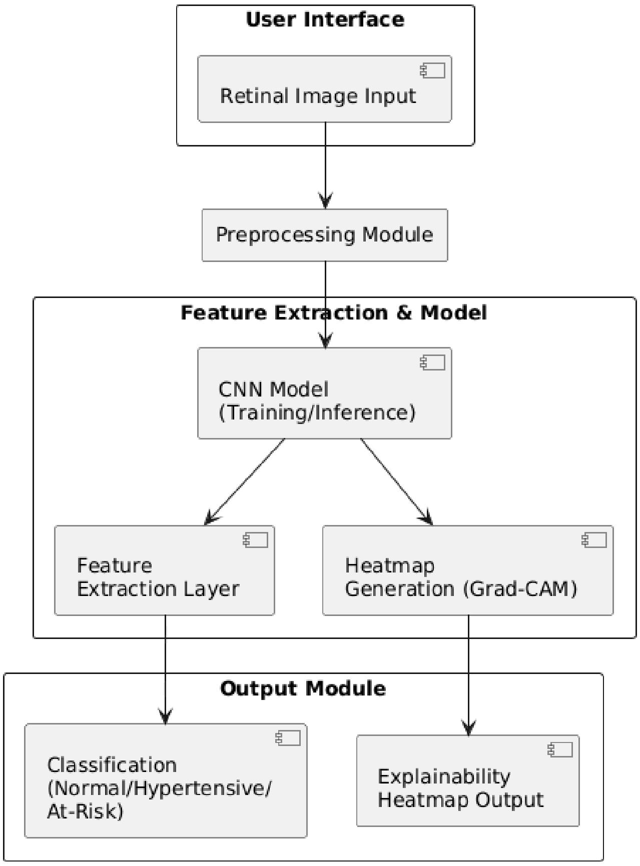

Fig. 1: System Architecture

A. Dataset Acquisition

The process of obtaining datasets entails gathering high-quality retinal fundus photos from known public repositories. These include the DRIVE, STARE, and Messidor databases, as well as the ODIR and Kaggle collections. These datasets together give a wide range of retinal appearances, including healthy eyes, minor blood vessel abnormalities, and extensive disease-related alterations. Images are collected in established formats and meticulously organized to ensure uniformity throughout the processing stages. Including a variety of patient demographics, imaging instruments, and lighting conditions is crucial for making the model more broadly applicable. Before being added to the project repository, each dataset is carefully assessed. This assessment focuses on its clarity, the usefulness of its annotations, and how well it represents the specific pathological conditions. The images obtained serve as the foundation for segmentation, preprocessing, training, and evaluation in the next stages.

B. Data Collection Challenges

Data gathering is often hindered by technical and clinical problems, particularly due to differences between datasets. Many existing datasets were originally created to help with diabetic retinopathy or general eye disease identification. As a result, they typically lack complete or accurate information about hypertension or cardiovascular problems. Manual verification and relabeling are necessary steps to provide consistent diagnostics. Differences in resolution, contrast, brightness, and camera type among the photographs create variables that could negatively affect how well the model learns, unless these differences are rectified. Another important issue is class imbalance, because pictures of the retina connected to hypertension and heart attacks are rather rare. Therefore, careful dataset preparation, aligning datasets, and thorough quality checks are essential before starting model building.

C. Data Augmentation

Data augmentation increases the size of the dataset, which improves the model's ability to generalize to retinal images it hasn't seen before. Rotational augmentation simulates multiple camera angles, whereas horizontal and vertical flips represent natural differences in how the eyes are positioned. By using scaling and zooming, the model can distinguish arteries and lesions at different magnification levels. This reduces the impact of changes in image resolution. By adjusting brightness and contrast, the model may learn to deal with the many lighting situations often found in clinical imaging. This regulated randomization delivers useful diversity while preserving the retina's basic anatomical structure. As a result, the enhanced dataset becomes more varied. This reduces overfitting and increases the CNN's robustness.

D. Preparing Retinal Images

Preprocessing prepares retinal pictures to help extract features more effectively by leveling the visual properties throughout the entire dataset. Converting to grayscale accentuates structural information while also minimizing the computational cost. Image scaling ensures that all samples have the same input dimensions, which is necessary for Convolutional Neural Network (CNN) designs. Using U-Net or Frangi filters for vessel segmentation isolates blood vessels.

This allows the model to focus on important microvascular patterns. Contrast enhancement using CLAHE exposes tiny differences, such as the narrowing of small blood vessels or the presence of microaneurysms. These filters reduce sensor noise and uneven lighting, while also keeping the important edges of the vessels. Finally, normalizing pixel values helps to stabilize the training process by guaranteeing constant intensity distributions. These preprocessing steps together generate uniform, high-quality inputs for the deep-learning model.

E. Model Preparation and Training

The process of preparing and training a model is a critical step. It involves several key stages. Preparing the model requires setting up a Convolutional Neural Network (CNN) designed to extract features from retinal microvasculature and classify diseases. To ensure reliable evaluation of prediction performance, the preprocessed images are separated into training, validation, and testing sets. The convolutional neural network (CNN) learns to identify morphological features, such as vascular width, twisting, the ratio of arteries to veins, and patch-like patterns, which are related with high blood pressure or heart problems. To improve the reliability of convergence, by using optimization tactics such adaptive learning rates, regularization, and dropout. Weighted loss functions help to alleviate class imbalance by giving more attention to images of cardiovascular-risk factors that are less common. The training process continues until the model's accuracy stabilizes and overfitting is reduced. The resulting model provides a reliable classification tool, capable of identifying minor changes in blood vessels.

F. Outcome and Understanding

The final step involves using the trained convolutional neural network (CNN) to analyze new retinal images, which then produces diagnostic predictions about the risk of hypertension and heart attacks. The system's output includes classification labels that indicate whether a subject is normal, hypertensive, or at danger. To maintain transparency and build trust in clinical settings, we use heatmap-based explainability. This method uses gradient-based visualization techniques to highlight the areas that most influence the convolutional neural network's (CNN) decisions. These areas commonly appear at points where blood vessels split, in restricted little arteries, or where the blood vessels have unusual shapes. The interpretability aspect helps clinicians understand how the model works, which boosts its medical credibility. The diagnostic findings and heatmaps are provided through an interface designed to effectively express results. This supports early diagnosis, patient monitoring, and the use of scalable cardiovascular screening methods.

Result and Discussion

The findings of the suggested deep-learning system, which is based on retinal images, are shown first by summarizing the performance. This is followed by a detailed explanation of how data collection, preprocessing, segmentation, and classification worked together to achieve the final accuracy and evaluation. To ensure the model's broad applicability across different demographic groups and imaging methods, the system was trained on a diverse variety of retinal datasets. These datasets included DRIVE, STARE, Messidor, ODIR, and pictures from Kaggle.

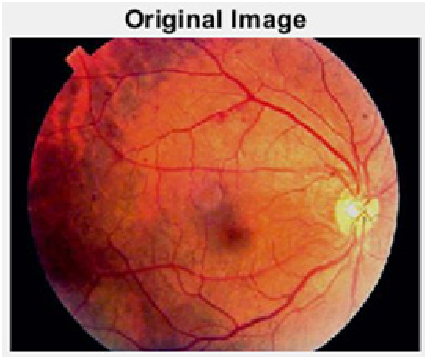

Fig. 2: Dataset

From figure 2, the dataset included a wide range of images, showing both normal and dysfunctional blood vessel conditions. This allowed the model to learn about subtle signals connected to high blood pressure and the risk of heart attacks. The varied methods used to gather data were crucial in creating a classifier that was both reliable and effective. This classifier could then identify microvascular problems linked to systemic cardiovascular stress. The model's ability to perform well in real-world screening scenarios was enhanced by the variety of resolutions, lighting conditions, and picture formats used.

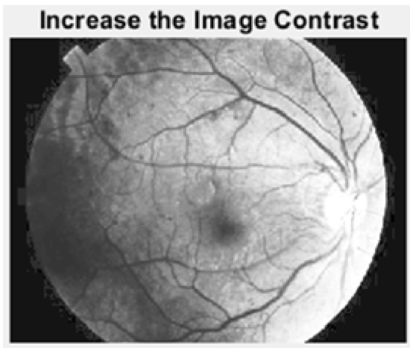

Fig. 3: Preprocessing

As on figure 3, before the segmentation and classification steps, preprocessing was important for normalizing and improving all retinal pictures. To improve the visibility of blood vessels, we used techniques like contrast-limited adaptive histogram equalization. At the same time, we applied noise-reduction filters to remove any unwanted elements that could interfere with finding the blood vessels. By normalizing the data, a consistent pixel intensity distribution was achieved across all datasets. This prevented variances in lighting from affecting the model's learning process. By replicating real-world differences, data augmentation methods including rotations, flips, and small geometric changes helped the system generalize better. By using these preprocessing processes, the neural network could learn vascular patterns, which helped reduce background noise and camera-related distortions. This, in turn, improved the stability and interpretability of the classifications.

The segmentation of retinal blood vessels significantly improved the model's performance. The segmentation network, which used deep learning, separated blood veins from other structures. This process removed distractions including the brightness of the optic disc, pigmentation patterns, and non-vascular textures as shown in figure 4.

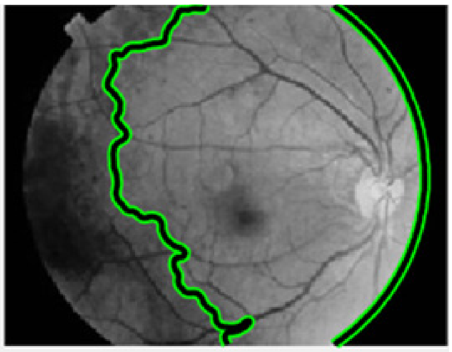

Fig. 4: Segmented image

Using the segmented vascular maps, the classifier may focus on the geometry of arterioles and venules, including their tortuosity, branching angles, and the complexity of their bifurcations. These vascular indications are commonly recognized as signs of hypertensive retinopathy and overall cardiovascular strain. The segmentation results improved the clarity of the heatmaps created later in the investigation. This was because the interpretability methods emphasized clinically important structures without being impacted by nearby retinal areas.

From figure 5, the classification stage uses a carefully designed Convolutional Neural Network (CNN) to identify images as either normal, hypertensive, or at risk for

Fig. 5: Classified image

cardiovascular problems. Through repeated training cycles, the classifier learned to recognize complicated connections between the structure of small blood vessels and general health. To prevent overfitting, the model was improved utilizing balanced sampling, planned learning-rate changes, and dropout regularization. The capacity to identify small details, such as localized narrowing, venular dilatation, enhanced vascular twisting, and unusual branching patterns, allowed for highly accurate predictions. Heatmap display enhanced the system's explainability, continuously highlighting arteriovenous junctions, vascular bifurcation areas, and locations exhibiting hemodynamic stress; this, in turn, bolstered its clinical dependability.

The results showed extraordinarily good performance metrics across all assessed categories. The system's total accuracy was 99.67%, proving its efficiency in detecting vascular patterns related to hypertension and the risk of heart attacks. The model achieved a precision of 99.52%, which meant that it rarely misclassified aberrant photos as healthy. The model showed a high level of accuracy, with both recall and sensitivity at 99.61% as shown in figure 6.

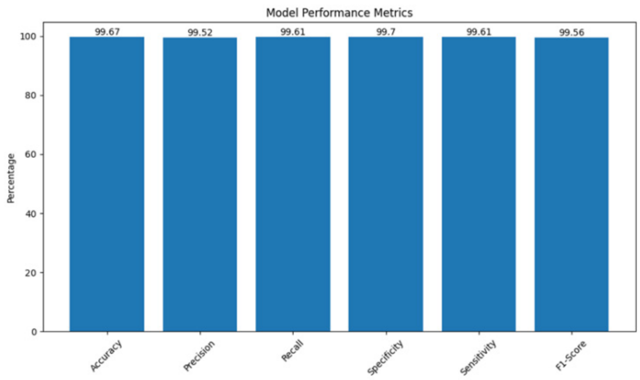

Fig. 6: Performance metrics

This means it could identify almost all actual abnormal instances, and it was also good at catching early indicators of the disease. The high specificity of 99.70%

indicates that there were very few false positives among the participants who were not affected. The F1-score, which was 99.56%, showed a good balance between precision and recall. At the same time, the AUC-ROC value of 0.998 indicated almost faultless capacity to distinguish between classes. Heatmaps regularly showed blood vessel problems, as described in eye care research. These included small arteries, enlarged veins, and unusual branching patterns in those with high blood pressure or other risk factors. These findings together demonstrate that the approach offers a highly reliable, easily understood, and non-invasive way to assess cardiovascular risk early, using retinal imaging.

Conclusion

This study's main finding highlights the usefulness of analyzing retinal images as a strong, non-invasive method for diagnosing both high blood pressure and the risk of heart attacks, using deep learning methods. Using a combination of different retinal datasets, careful preprocessing, and a proprietary convolutional neural network (CNN) design, the system reliably diagnoses microvascular problems related to cardiovascular issues. The research shows that the blood vessels in the retina carry important diagnostic information. This information may be efficiently analyzed using artificial intelligence models, which supports early identification in both clinical and resource-limited settings. The practical implications are important, as the system offers a readily available screening method. This method lowers the need for invasive procedures, specialized equipment, and subjective clinical evaluations. The ability to create understandable heatmaps enhances clinical trust by showing the specific body areas that influence the forecasts. Therefore, the suggested framework is a good tool for screening populations and continuously monitoring individuals at risk of cardiovascular problems. Future research could focus on increasing the variety of datasets, including different types of clinical data, and improving the ability to deploy solutions in real time. Further study could explore sophisticated architectures, hybrid diagnostic models, and enhanced methodologies for explainability. These efforts would aim to improve predicted accuracy and clinical usefulness.

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