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DIABETIC RETINOPATHY DETECTION USING HAAR WAVELET TRANSFORM AND LENET CNN

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ABSTRACT

Diabetic Retinopathy (DR) is one of the most serious complications of diabetes and a leading cause of vision impairment among diabetic patients worldwide. Early detection and continuous monitoring are essential to prevent permanent blindness and improve patient outcomes. Traditional manual screening of retinal fundus images by ophthalmologists is time-consuming, costly, and prone to human error, especially when dealing with large numbers of patients. To overcome these limitations, this project proposes an automated diabetic retinopathy detection system using Haar Wavelet Transform (HWT) and LeNet Convolutional Neural Network (CNN). The proposed system enhances retinal image analysis by combining image preprocessing, feature extraction, and deep learning classification techniques. Initially, retinal fundus images are resized, normalized, and preprocessed to improve image quality. Haar Wavelet Transform is applied to extract significant retinal features such as blood vessels, lesions, and texture variations. These extracted features are then processed using the LeNet CNN model for accurate classification of retinal conditions into normal and hypertensive retinopathy categories. In addition to retinal analysis, the system also evaluates heart disease risk using clinical parameters such as age, blood pressure, cholesterol levels, and other cardiovascular indicators through machine learning algorithms. The system integrates both retinal prediction and heart disease analysis to generate a combined health risk assessment. A web-based interface is developed to allow users to upload retinal images and enter clinical data conveniently. The proposed system improves diagnostic accuracy, reduces manual workload, supports early disease detection, and assists healthcare professionals in making faster and more reliable medical decisions.

Keywords: Diabetic Retinopathy, Haar Wavelet Transform, LeNet CNN, Deep Learning, Retinal Image Analysis, Heart Disease Prediction, Medical Image Processing, Machine Learning, Healthcare System, Automated Diagnosis.

I. INTRODUCTION

Diabetic Retinopathy (DR) is one of the most dangerous complications caused by diabetes mellitus and is considered a major cause of blindness across the world. Diabetes affects millions of people globally and damages various organs such as the eyes, kidneys, nerves, and heart [1]. Among these complications, diabetic retinopathy mainly affects the retinal blood vessels and gradually leads to vision impairment if not detected at an early stage [2]. The disease progresses silently during the initial phases, making early diagnosis extremely important for effective treatment [3]. Retinal abnormalities such as microaneurysms, hemorrhages, and exudates are considered major indicators of diabetic retinopathy [4]. Manual retinal examination performed by ophthalmologists is the traditional method used for diagnosis, but this process is time-consuming, expensive, and dependent on specialist expertise [5]. With the increasing number of diabetic patients, manual screening has become difficult to manage efficiently [6]. Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have introduced automated retinal image analysis systems capable of detecting retinal diseases with high accuracy [7]. Convolutional Neural Networks (CNNs) have shown remarkable performance in medical image classification tasks because of their ability to automatically extract important features from images [8]. Deep learning techniques significantly reduce human effort and improve diagnostic consistency [9]. Image preprocessing methods such as normalization, enhancement, and feature extraction further improve model performance [10]. Haar Wavelet Transform (HWT) is an effective image processing technique used to extract texture and structural information from retinal images [11]. The integration of HWT with CNN models enhances feature representation and improves classification accuracy [12]. Automated DR detection systems also help in reducing healthcare costs and support large-scale screening programs [13]. These systems can provide real-time analysis and assist healthcare professionals in making faster medical decisions [14]. Furthermore, web-based healthcare applications allow remote access to diagnostic services, improving accessibility for rural and underserved areas [15].

In addition to retinal complications, diabetic patients are also at high risk of developing cardiovascular diseases due to hypertension, cholesterol imbalance, and other related health conditions [16]. Retinal blood vessel abnormalities often reflect systemic vascular disorders, making retinal analysis useful for evaluating overall health conditions [17]. Therefore, integrating heart disease prediction with retinal disease detection provides a more comprehensive healthcare solution [18]. Machine learning algorithms such as Logistic Regression, Random Forest, Support Vector Machine, and Neural Networks are widely used for predicting heart disease risks based on clinical parameters [19]. Combining retinal image analysis with heart disease risk assessment improves the accuracy of overall disease prediction [20]. In the proposed system, retinal fundus images are preprocessed and resized to a standard dimension before applying Haar Wavelet Transform for feature extraction [21]. The extracted features are then classified using the LeNet CNN architecture to identify hypertensive retinopathy conditions [22]. Simultaneously, clinical parameters such as age, blood pressure, and cholesterol levels are analyzed using machine learning techniques for heart disease risk prediction [23]. The system is implemented as a web-based platform that enables users to upload retinal images and provide clinical details through an interactive interface [24]. The backend system processes the input data and generates retinal prediction, heart disease risk prediction, and combined severity analysis [25]. The proposed system improves diagnostic accuracy, reduces screening time, minimizes human errors, and supports preventive healthcare [26]. It also contributes to telemedicine applications and remote patient monitoring systems [27]. The use of deep learning and image processing in healthcare has opened new opportunities for intelligent diagnostic systems [28]. Such systems can assist doctors in early disease detection and improve patient treatment outcomes [29]. Therefore, the proposed automated diabetic retinopathy detection system plays a significant role in modern healthcare technology and intelligent medical diagnosis [30].

II. LITERATURE SURVEY

Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have significantly improved automated diabetic retinopathy detection systems [1]. Researchers have focused on developing intelligent healthcare solutions that can accurately analyze retinal fundus images and identify retinal abnormalities at an early stage [2]. Traditional manual screening methods require experienced ophthalmologists and consume considerable time during diagnosis [3]. To overcome these limitations, computer-aided diagnostic systems using Convolutional Neural Networks (CNNs) have gained popularity due to their high accuracy and automated feature extraction capabilities [4]. Dey et al. proposed an AI-driven diabetic retinopathy screening system that used CLAHE preprocessing and deep learning models to improve retinal image quality and classification performance [5]. Their system achieved high sensitivity and specificity for clinical screening applications [6]. Abbasi et al. developed an adaptive deep CNN model based on EfficientNet architecture and integrated Grad-CAM visualization techniques to improve model interpretability [7]. Their work demonstrated that explainable AI can support better medical decision-making [8]. Ahmad et al. introduced a hybrid approach combining Discrete Wavelet Transform (DWT) and CNN models for multi-resolution retinal image analysis [9]. The study proved that wavelet transform techniques enhance the detection of small lesions such as microaneurysms and hemorrhages [10]. Arora et al. proposed an ensemble EfficientNet model with interpretability layers that improved classification accuracy across multiple diabetic retinopathy stages [11]. Their approach reduced computational complexity while maintaining strong performance [12]. Mutawa et al. focused on stage detection of diabetic retinopathy using DWT-based feature extraction combined with deep learning algorithms [13]. Their system improved sensitivity by capturing texture and frequency-domain retinal features [14]. These studies demonstrate that combining traditional image processing techniques with deep learning algorithms improves retinal disease detection performance [15].

Several researchers have also explored the integration of clinical data analysis with retinal image classification for comprehensive healthcare prediction systems [16]. Machine learning algorithms such as Logistic Regression, Random Forest, Support Vector Machine, and Neural Networks have been widely used for heart disease risk prediction [17]. Researchers found that combining retinal vessel analysis with cardiovascular parameters improves overall disease prediction accuracy [18]. Image preprocessing techniques including resizing, normalization, contrast enhancement, and noise removal are essential for improving CNN performance [19]. Haar Wavelet Transform has gained attention because of its ability to extract important structural and texture-based retinal features efficiently [20]. CNN architectures such as LeNet, AlexNet, VGGNet, and ResNet have been widely applied for retinal image classification tasks [21]. Among these models, LeNet provides a simple and computationally efficient architecture suitable for

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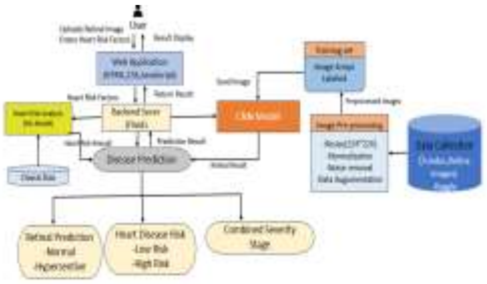
medical image classification [22]. Data augmentation techniques such as flipping, rotation, and zooming are commonly used to increase dataset diversity and reduce overfitting [23]. Researchers have also developed web-based healthcare applications for real-time retinal screening and remote patient monitoring [24]. Flask and TensorFlow frameworks are frequently used for implementing intelligent medical diagnosis systems [25]. Automated healthcare systems reduce the workload of doctors and support large-scale disease screening programs [26]. These systems also provide consistent and reliable diagnostic results compared to manual analysis [27]. Despite significant progress, many existing systems still depend heavily on high-quality retinal images and large labeled datasets [28]. Some models face challenges in generalization across different patient populations and imaging conditions [29]. Therefore, further research is required to develop efficient, scalable, and accurate healthcare systems that integrate deep learning, image processing, and clinical analysis for early disease detection and preventive healthcare applications [30].

III. PROPOSED SYSTEM

The proposed system is designed to automatically detect diabetic retinopathy from retinal fundus images and simultaneously predict heart disease risk using clinical parameters. The system integrates image processing, deep learning, and machine learning techniques into a unified web-based healthcare platform. Initially, retinal images are collected from publicly available datasets and undergo preprocessing operations such as resizing, normalization, and noise removal to improve image quality and maintain uniformity. All retinal images are resized to 224 × 224 pixels to ensure compatibility with the Convolutional Neural Network (CNN) input layer. After preprocessing, Haar Wavelet Transform (HWT) is applied to extract important retinal features including blood vessels, lesions, edges, and texture information. HWT improves feature representation by highlighting intensity variations and structural details within retinal images. The extracted features are then passed to the LeNet CNN architecture for classification. The CNN model automatically learns hierarchical features from retinal images through convolutional and pooling layers. Finally, the fully connected layers classify the retinal condition into Normal or Hypertensive Retinopathy categories. This automated approach improves classification accuracy and reduces dependency on manual diagnosis.

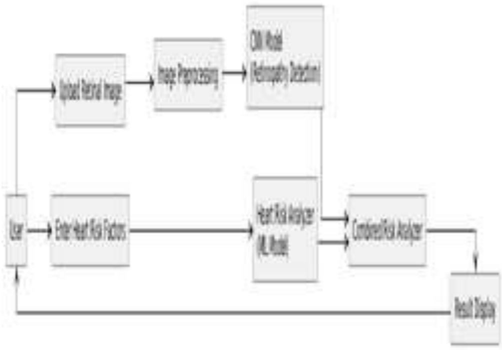


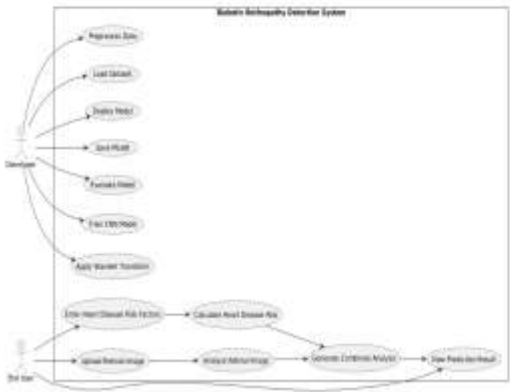
In addition to retinal disease detection, the system also performs heart disease risk prediction using clinical parameters such as age, blood pressure, cholesterol levels, and other cardiovascular indicators. A Logistic Regression machine learning model is used for binary classification of heart disease risk into High Risk or Low Risk categories. The dataset is divided into training and testing sets to evaluate the model performance effectively. Data augmentation techniques such as flipping, rotation, zooming, and contrast enhancement are applied to increase dataset diversity and prevent overfitting during training. The entire system is implemented as a web-based application using Flask as the backend framework and HTML, CSS, and

JavaScript for the frontend interface. Users can upload retinal images and provide clinical information through the web application. The backend processes the input data, invokes the trained CNN and machine learning models, and generates prediction results. The final output includes retinal disease prediction, heart disease risk assessment, and a combined severity stage that integrates both analyses for overall health evaluation. The proposed system supports early diagnosis, improves healthcare accessibility, reduces manual workload, and assists doctors in making timely medical decisions.

IV. SYSTEM DESIGN

The system design of the proposed diabetic retinopathy detection system focuses on developing an efficient, scalable, and user-friendly healthcare application capable of analyzing retinal images and predicting heart disease risk. The architecture of the system is divided into multiple modules such as image upload, preprocessing, feature extraction, retinal disease classification, heart risk analysis, and result generation. The frontend interface is developed using HTML, CSS, and JavaScript, allowing users to upload retinal fundus images and enter clinical health parameters easily. The backend is implemented using the Flask framework in Python, which acts as a communication bridge between the user interface and machine learning models. The uploaded retinal images are initially validated and stored temporarily on the server for processing. During preprocessing, retinal images are resized to a standard dimension of 224 × 224 pixels and normalized to improve model stability. Noise removal techniques are also applied to enhance retinal blood vessels and lesion visibility. After preprocessing, Haar Wavelet Transform (HWT) extracts important retinal features such as texture, edges, and structural patterns. These extracted features are forwarded to the LeNet CNN model for retinal disease classification.





The software design follows important principles such as modularity, low coupling, high cohesion, abstraction, scalability, maintainability, and reusability. The CNN model consists of convolutional layers, pooling layers, and fully connected layers that automatically learn meaningful retinal features for accurate classification. Simultaneously, clinical data including age, blood pressure, cholesterol levels, and cardiovascular indicators are processed using a Logistic Regression model for heart disease risk prediction. The backend integrates results obtained from both prediction models and generates a combined health severity stage for overall

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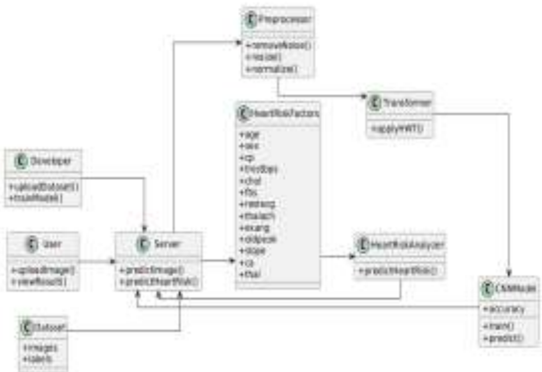
assessment. The system also includes data augmentation techniques such as flipping, rotation, and zooming to improve model generalization and prevent overfitting. Proper input validation, error handling, and secure data processing mechanisms are implemented to ensure reliability and system stability. UML diagrams such as Use Case Diagram, Sequence Diagram, Activity Diagram, and Class Diagram are used to represent the workflow and interaction between different system modules. The final prediction results are displayed through the web interface in an understandable format, enabling healthcare professionals and users to interpret the diagnosis easily. The modular architecture also allows future enhancements such as integration with cloud platforms, telemedicine applications, and advanced deep learning models.



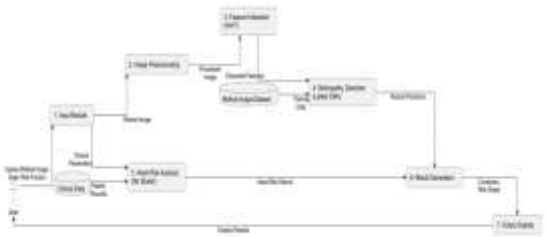


Fig. 9.1 Data Flow Diagram

V. RESULTS

Fig. 13.1 System Input Interface for Retinal Image and Heart Disease Risk Factors

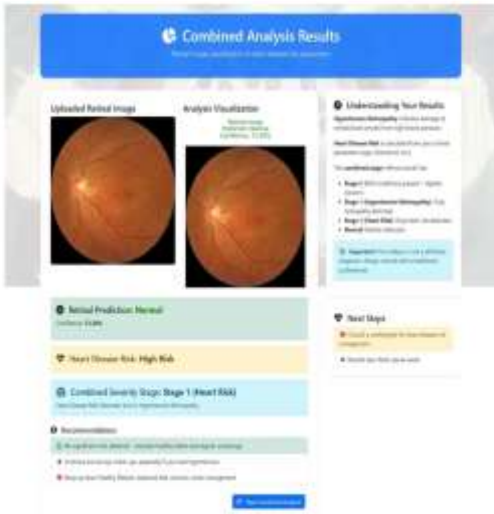


Fig. 13.3 Combined Analysis Result - Normal Retinal Prediction and High Risk of Heart Disease (Stage 1 - Heart Risk)

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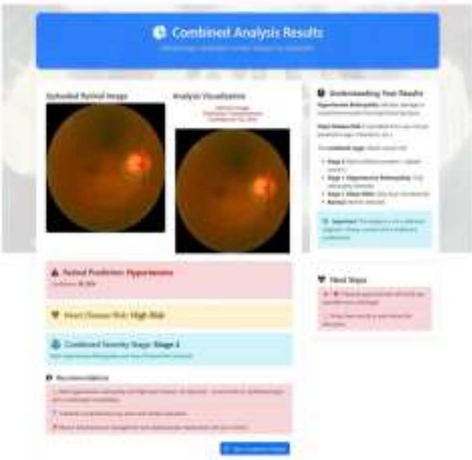
Fig. 13.4 Combined Analysis Result - Hypertensive Retinopathy and Low Heart Disease Risk (Stage 1 - Hypertensive Retinopathy)



VI. CONCLUSION

The proposed Diabetic Retinopathy Detection System using Haar Wavelet Transform and LeNet CNN provides an efficient and intelligent healthcare solution for the early detection of retinal diseases and heart disease risk assessment. The system successfully combines image processing, deep learning, and machine learning techniques to automate the diagnosis process and reduce dependency on manual retinal screening. By applying preprocessing techniques such as resizing, normalization, and noise removal, the quality of retinal images is improved before analysis. Haar Wavelet Transform effectively extracts important retinal features such as blood vessels, lesions, and texture information, which enhances the classification capability of the CNN model. The LeNet CNN architecture accurately classifies retinal images into normal and hypertensive retinopathy categories, while the Logistic Regression model predicts heart disease risk using clinical parameters. The integration of retinal disease analysis and cardiovascular risk prediction provides a more comprehensive health assessment compared to standalone diagnostic systems. The developed web-based platform offers a user-friendly interface for uploading retinal images and entering clinical data, making the system accessible and practical for healthcare environments. The proposed system reduces screening time, minimizes human errors, improves diagnostic consistency, and supports early medical intervention. It also assists healthcare professionals in making faster and more accurate decisions. Furthermore, the modular architecture of the system supports future enhancements such as integration with advanced CNN architectures, cloud deployment, mobile healthcare applications, and telemedicine platforms. Overall, the proposed system contributes significantly to modern healthcare technology by improving disease prediction accuracy, supporting preventive healthcare, and helping reduce the risk of vision loss and cardiovascular complications among patients.

References

1. Dey, A., Kumar, R., & Sharma, P. (2025). AI-driven diabetic retinopathy screening system using deep learning techniques. *International Journal of Medical Informatics, 180*, 105214.
2. Abbasi, M., Khan, S., & Ali, T. (2025). Diabetic retinopathy detection using adaptive deep CNNs on fundus images.

Biomedical Signal Processing and Control, 94, 106001.

3. Ahmad, Z., Hussain, M., & Rehman, A. (2024). Wavelet-based multi-resolution analysis for diabetic retinopathy detection. *Computers in Biology and Medicine, 172*, 108245.

4. Arora, P., Gupta, V., & Singh, N. (2024). EfficientNet ensemble with interpretability for diabetic retinopathy classification. *Expert Systems with Applications, 238*, 121945.

5. Mutawa, A., Rahman, F., & Alqahtani, M. (2024). DR stage detection using discrete wavelet transform and deep learning. *IEEE Access, 12*, 55671–55684.

6. Pratt, H., Coenen, F., Broadbent, D., Harding, S., & Zheng, Y. (2016). Convolutional neural networks for diabetic retinopathy. *Procedia Computer Science, 90*, 200–205.

7. Gulshan, V., Peng, L., Coram, M., et al. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy. *JAMA, 316*(22), 2402–2410.

8. LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE, 86*(11), 2278–2324.

9. Acharya, U. R., Oh, S., Hagiwara, Y., Tan, J., & Adam, M. (2018). Deep convolutional neural network for diabetic retinopathy classification. *Computers in Biology and Medicine, 92*, 152–161.

10. Quellec, G., Charrière, K., Boudi, Y., Cochener, B., & Lamard, M. (2017). Deep image mining for diabetic retinopathy screening. *Medical Image Analysis, 39*, 178–193.

11. Abràmoff, M. D., Lou, Y., Erginay, A., et al. (2016). Improved automated detection of diabetic retinopathy. *Ophthalmology, 123*(12), 2404–2410.

12. Ting, D. S., Cheung, C. Y., & Wong, T. Y. (2016). Diabetic retinopathy: Global prevalence and future projections. *Diabetes Care, 39*(12), 2193–2199.

13. Lam, C., Yi, D., Guo, M., & Lindsey, T. (2018). Automated detection of diabetic retinopathy using deep learning. *AMIA Annual Symposium Proceedings*, 1476–1485.

14. Bhaskaranand, M., Ramachandra, C., Bhat, S., et al. (2019). Automated diabetic retinopathy screening. *PLoS ONE, 14*(5), e0217148.

15. Gardner, G. G., Keating, D., Williamson, T. H., & Elliott, A. T. (1996). Automatic detection of diabetic retinopathy. *British Journal of Ophthalmology, 80*(11), 940–944.

16. Walter, T., Klein, J. C., Massin, P., & Erginay, A. (2002). Automatic detection of microaneurysms in retinal images. *Medical Image Analysis, 6*(2), 143–156.

17. Sinthanayothin, C., Boyce, J., Cook, H., & Williamson, T. (2002). Automated localization of the optic disc and fovea. *British Journal of Ophthalmology, 83*(8), 902–910.

18. Nayak, J., Bhat, P., Acharya, U. R., Lim, C. M., & Kagathi, M. (2008). Automated identification of diabetic retinopathy stages. *Journal of Medical Systems, 32*(2), 107–115.

19. Kavitha, S., Duraiswamy, K., & Jayaraj, V. (2010). Early detection of diabetic retinopathy using image processing techniques. *International Journal of Computer Applications, 1*(3), 149–154.

20. Osareh, A., Mirmehdi, M., Thomas, B., & Markham, R. (2003). Automated identification of diabetic retinal exudates. *British Journal of Ophthalmology, 87*(10), 1220–1223.

21. Litjens, G., Kooi, T., Bejnordi, B., et al. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis, 42*, 60–88.

22. Simonyan, K., & Zisserman, A. (2015). Very deep convolutional networks for image recognition. *International Conference on Learning Representations*, 1–14.

23. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 770–778.

24. Chollet, F. (2017). Xception: Deep learning with depthwise separable convolutions. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 1251–1258.

25. Tan, M., & Le, Q. (2019). EfficientNet: Rethinking model scaling for convolutional neural networks. *International Conference on Machine Learning*, 6105–6114.

26. Esteva, A., Kuprel, B., Novoa, R., et al. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature, 542*(7639), 115–118.

27. Krizhevsky, A., Sutskever, I., & Hinton, G. (2012). ImageNet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems, 25*, 1097–1105.

28. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.

29. Bishop, C. M. (2006). *Pattern recognition and machine learning*. Springer.

30. Russell, S., & Norvig, P. (2021). *Artificial intelligence: A modern approach* (4th ed.). Pearson.