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Advanced Retinal Image Analysis for Cardiovascular Disease Risk Prediction Using Hybrid Deep Learning

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Abstract: Another reason of death in the world is still heart and blood vessel diseases and their early identification is highly significant in their treatment. The retinal fundus imaging is a painless method of examining the alterations in blood vessels of the heart that are as a result of heart conditions. Regular research methods will not, however, necessarily identify small patterns of blood vessels that indicate disease. Clinical features were obtained using retinal pictures by using Kaggle EyePACS dataset to enable multimodal prediction. In the preprocessing stage, the images were downsized, random horizontal flips and rotations were added, and transformed into tensors to be classified. Simultaneously, the files with detections were merged and configured to the object localization based on YOLO. The baseline classification models were ResNet50, VGG16, and a regular CNN, as well as the mixed EfficientNetV2 feature extractor, which is a combination of 1D CNN layers. Object recognition was done through YOLOv5, YOLOv8, YOLOv9, and YOLOv11 to identify and label issues. Accuracy, precision, recall, F1-score, specificity, sensitivity, and error were used to measure classification performance. Recognition was measured by precision, recall and mAP. The suggested hybrid classification model had the best accuracy (99.9%), as well as the best precision, F1-score, and specificity. YOLOv5 was the highest in terms of detection performance with a mAP of 0.787. The most significant areas to make predictions were demonstrated by means of GradCAM, and a web interface based on Flask allowed individuals to input data and view the outcomes in real-time. This was more predictive and localised the retinal issues on how to determine the early cardiovascular risk.

"Index Terms: *Retina , Heart , Feature extraction , Accuracy , Convolutional neural networks , Biomedical imaging , Risk management , Machine learning , Deep learning , Data models".*

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1. INTRODUCTION

It is not easy on people, healthcare systems, and businesses because heart disease remains one of the primary causes of morbidity and mortality in the world [1]. Early detection of people at high risk is highly essential in reducing avoidable deaths and improved outcomes over a long period [2]. The traditional methods of diagnosis and risk assessment are invasive tests, lab tests, and imaging tests, which are difficult to access, costly, or unavailable in resource-poor locations [3]. The advancements in medical imaging and AI have provided the possibility to quantify risk in the absence of surgery, particularly the retinal imaging, which reveal the state of the blood vessels in the whole body [4]. Retinal microvasculature is a tool that is helpful in forecasting the future and most of its changes in structure and functionality are associated with heart issues [5].

Although the analysis of retinal images is gaining popularity as a method of examining the health condition of the heart, the study has a number of serious issues that complicate its application in the real world [6]. Many studies are just searching the general issues with the arteries and do not actually investigate the question of how to categorize all the risks of heart disease [7]. Stated results can hardly be reliable and extrapolable to other conditions due to the lack of diversity in data sets, small sample sizes, and lack of diversity in populations [8]. In addition, previous research tended to consider imaging data individually, without considering the larger clinical context that is required to provide accurate risk assessment [9]. These gaps demonstrate the value of having a larger, more versatile study design that can locate little, clinically significant indications of heart disease risk in retinal images [10].

Due to these issues, the objective of the study is to design a powerful retinal image-based system to determine the risk of heart disease in a broad category of individuals. In this study, the chief objective will be to establish the extent to which retinal characteristics can be utilized to determine cardiovascular risk in a reliable and systematic manner. This work aims at improving representations of retinal patterns which are clinically significant, and it ends up being more useful to a broader demographic, and determining how to successfully integrate more health information where available. The paper is expected to shift the retinal imaging field of the exploratory analysis to the field of practical cardiovascular risk assessment by attentively examining the data variety and model explanability.

This research is significant as it may result in non-invasive, easily accessible, and cheap screening of cardiovascular threat with the help of already made pictures of the retina. The approach could facilitate the earlier intervention, individual prevention strategies, and clinical decision-making improvement, particularly in the settings where the access to professional diagnostic means is low. The proposed work will assist in uniting the field of ophthalmology with cardiology because retinal imaging will be more evidence-based during cardiovascular evaluation. Finally, the study may alter the process of screening in the future and help to provide equitable and evidence-based cardiovascular care globally.

2. LITERATURE REVIEW

It is not easy on people, healthcare systems, and businesses as heart disease remains one of the primary causes that make people sick and die all over the world [1]. Early identification of people at high risk is highly significant in reducing avoidable and preventable deaths and improved long-term outcomes [2]. Conventionally diagnosed methods of risk evaluation and assessment rely on invasive tests, laboratory tests, and imaging procedures, which are difficult to access, costly, or unavailable in low-resource locations [3]. The advancement of medical imaging and AI has enabled the possibility to assess risk without surgery, particularly with the retinal imaging, which demonstrates the healthiness of the blood vessels all over the body [4]. The retinal microvasculature is a useful tool as it demonstrates alteration of structure and functionality of the retinal microvasculature which is associated with heart issues in predicting the future [5].

Although the retinal image analysis is increasingly gaining popularity as a method of examining the condition of the heart, there are significant issues with the research which render it difficult to apply in practice [6]. Most of the research simply seeks general issues with the arteries and does not actually investigate how to categorize all the risks of heart disease [7]. It is difficult that the stated results can be reliable and relevant to other circumstances as the datasets are not very diverse, the sample sizes are small, and the population is not very different [8]. Furthermore, previous investigations usually examined imaging data in isolation, without considering the higher clinical context that requires to be assessed properly to determine the risk [9]. These gaps reveal the significance of the bigger and more adaptable study model capable of identifying tiny and clinically significant indications of heart disease hazard in the retinal pictures [10].

Due to these issues, the aim of the study is to develop an influential retinal image-based system to determine the risk of heart disease in a broad group of individuals. The primary objective of this research with this study is to determine how the retinal features can be utilized to reliably and systematically estimate cardiovascular risk. This research is aimed at improving the representations of retinal patterns that are clinically relevant, the results of the research are more relevant to more demographic groups, and determining how best to combine other health information when it is available. The research will help to transform retinal imaging into more than a mere exploratory study into the practical cardiovascular risk assessment by attentively examining data heterogeneity and model explanability.

The significance of this study is that it might result in non-invasive, non-invasive, and inexpensive screening of cardiovascular risk with the images of the retina, which are already taken. This approach may aid in the earlier intervention, individualized prevention strategies, and improved clinical decision-making, particularly in the locations where the access to expert diagnostic resources is not available. The proposed work assists in uniting ophthalmology and cardiology since retinal imaging is more evidence-based in cardiovascular assessment.

Ultimately, this research may transform the manner in which screening will be conducted in future and contribute to justifiable and data-driven cardiovascular healthcare in the global context.

3. MATERIALS AND METHODS

The given approach is supposed to calculate the cardiovascular risk of a person using the retinal fundus images and clinical data provided through the EyePACS dataset. This will enable multimodal and non-invasive assessment framework. The overall algorithm is the integration of retinal images and normalized clinical characteristics that aid in the learning along with the correct identification of risk. The baseline DL models are then tested to provide a standard of performance. A hybrid design is then applied to enhance the capacity to make the distinction between things through a mixture of deep visual feature extraction and clinical feature modeling. In order to make the framework even more solid, the addition of object recognition models based on Yolo is also introduced to locate the problems in the retina more precisely. The framework is then made more visual using GradCAM which highlights areas that are important in influencing predictions. The model is more reliable because cross-validation and extensive performance assessment on the basis of several classification measures are performed. Flask-based deployment interface also allows users to interact and make conclusions in real-time. This approach allows predictions to be more precise, intuitive as well as scalable simultaneously. It is a convenient and simple method of cardiovascular risk measurement.

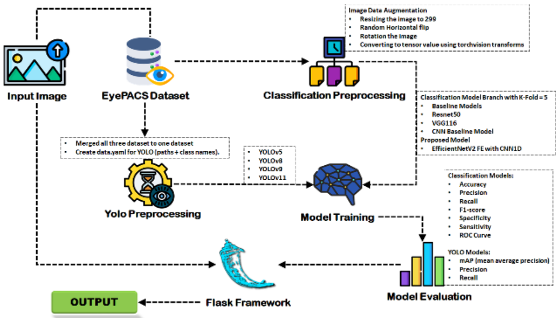


Fig.1 Proposed Architecture

The proposed system architecture will involve fundus images and clinical features, which will be automatically used to measure the risk of eye diseases. Picture classification and object detection can be assisted with the aid of preparing a dataset. An algorithm based on CNN can inform you about the risk of your heart, and the algorithm based on YOLO can detect the issues with your eyes. The inference pipeline is implemented on the back-end using the Flask, and the decisions are made using the trust and synthesizing the predictions of various sources. Front end displays the results and visual descriptions. Heatmaps (grad-CAM) are introduced to make the data more transparent, simple to interpret, and reliable to clinicians with the help of the decision support.

a) Dataset Collection:

The information that will be utilized in this study will be the EyePACS retinal fundus image collection. This warehouse contains numerous eye records that can be utilized to observe diseases in the entire body. It contains 6,000 samples and each of them is associated with a picture on the retina and a collection of clinical information accompanying it. The dataset includes images, diagnostic and risk labels, structured clinical features such as blood pressure, cholesterol, body mass index, glycated hemoglobin, diabetes state, smoking habit and age. This dataset is ideal in predicting multimodal cardiovascular risks and performing good model evaluation due to the presence of both imaging and clinical data and data splits which have already been configured.

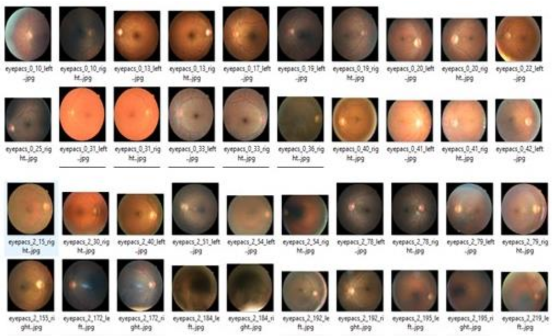


Fig.2 EyePACS Dataset

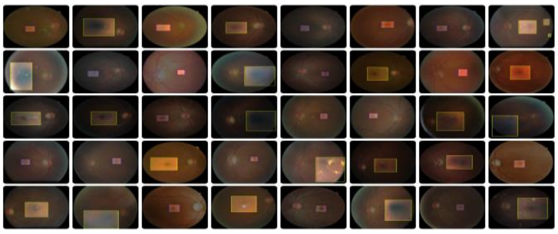


Fig .3

b) Pre-Processing:

Good preprocessing should be done to ensure that the information is consistent, the features are useful and also the model can be utilized by many people. This could be achieved by taking time to prepare clinical attributes and retinal images in order to predict strong and accurate cardiovascular risks.

Feature Selection: In this step, clinical attributes that are important to cardiovascular risk are identified and clustered. This forms an organized feature set. Part of these features include physiological measurements, living indicators, as well as demographic factors which are clinically significant in estimating risk. The goal label for cardiovascular risk is standardized to make sure that it is shown the same way in all samples. In scenarios where there are clinical data and retinal image data this is required in order to remove the noise, bring the features more useful and also enable the possibility of having reliable multimodal learning.

Image Preprocessing: Standardized preprocessing is done on retinal fundus images to make sure that the quality of the inputs is the same across the collection. The pictures are reduced in size to some extent and transformed into a typical number composition that can be utilized by models. Additional variation is added to the data controlled by geometric changes methods, preserving the clinical relevance. The step enhances model generalization, decreases overfitting and enhances robustness by training to simulate the dynamics of retinal image acquisition conditions in the real world.

Dataset Organization and Class Structuring: The data set is structured in a manner that it makes sense in the cardiovascular risk groups. It is disaggregated into class-based directories. The identifiers of images are standardized such that a standard association between retinal images and medical information that accompanies them exists. In order to permit binary risk classification, definite classifications are established. Such a structured arrangement ensures the appropriate labels are assigned, data are able to be retrieved in a short time and there is no misunderstanding regarding the classes. It is now possible to train and test supervised learning models in a controlled laboratory environment.

c) Algorithms:

Classification:

ResNet50: ResNet50 contains deep residual learning capabilities which assist it to train extremely deep networks in a secure manner. Its skip connections retain information about the features in multiple layers and this enables reconstruction of hierarchical retinal patterns with more reliability and enhances the performance of classification in terms of accuracy and generalizability.

VGG16: VGG16 architecture is the traditional convolutional architecture which employs homogeneous layered design to store spatial and textural characteristics in a gradual manner. Its discriminative characteristic extraction offers consistent convergence and correct baseline functionality in comparing the effectiveness of classification.

$$O_{i,j,k} = \sum_{m}\sum_{n}\sum_{c} X_{i+m,j+n,c} \;\; W_{m,n,c,k+} \, b_k \qquad (1)$$

CNN: The traditional Convolutional Neural Network assumes hierarchical convolution and pooling steps which allow computers to automatically discover how to distinguish the various visual features. It is rather rudimentary in design, however, effective as a training tool, and a benchmark on which the advantages of more profound and hybrid models can be evaluated.

$$S(i,j) = \sum_{m}\sum_{n} I(i+m, j+n) \cdot K(m,n) \qquad (2)$$

Extension:

YOLOv5: YOLOv5 is an object detector that is based on a single stage that is capable of localising and classifying objects simultaneously. It provides a good balance between speed and accuracy in detection and thus finds clinically important areas in the retina with high real time response.

$$x = \sigma(t_x) + C_x, \qquad y = \sigma(t_y) + C_y \quad (3)$$

YOLOv8: YOLOv8 enhances the precision of object identification facilitating more comfort of seeing and comprehending the location of objects in space. Due to its sophisticated design, one can precisely detect the issues in the retina and maintain quick inference and robust generalization in a broad set of conditions in a picture.

$$\mathcal{L} = \lambda_{box}\mathcal{L}_{box} + \lambda_{obj}\mathcal{L}_{obj} + \lambda_{cls}\mathcal{L}_{cls} \quad (4)$$

YOLOv9: YOLOv9 enhances the use of features to enhance the reliability and robustness of detection. It enables the reliable and repeated detection and labeling of small problems in the retina across a variety of imaging conditions through making internal representation learning more robust.

$$\mathcal{L}_{YOLOv9} = \lambda_{box}\mathcal{L}_{box} + \lambda_{obj}\mathcal{L}_{obj} + \lambda_{cls}\mathcal{L}_{cls} + \lambda_{dfl} + \mathcal{L}_{dfl} \quad (5)$$

YOLOv11: YOLOv11 is more concerned with feature fusion that is advanced to enhance the stability and accuracy of recognition. It is useful in proper identification of small visual patterns, and therefore finding and comprehending regions of the retina associated with cardiovascular risk becomes easier.

4. EXPERIMENTAL RESULTS

Accuracy: The ability of a test to distinguish between ill and healthy individuals is referred to as its accuracy. In order to have a clue of the accuracy of a test we must estimate the percentage of true positives and true negatives. Mathematically this can be expressed as.

$$Accuracy = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \,(6)$$

Precision: Precision is the ratio of the number of cases or samples, which were correctly classified, to the number of cases or samples which were correctly classified as positive. Thus, the way to compute the precision is as follows:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} \,(7)$$

Recall: Recall is a metric in machine learning which measures the extent to which a model can identify all the significant examples of a particular class. It demonstrates the quality of a model in capturing the instances of a particular class. It is determined by dividing the correct predicted positive results by the overall number of the real positives.

$$Recall = \frac{\text{TP}}{\text{TP } + \text{ FN}} \,(8)$$

F1-Score: F1 score is a metric that can be used to measure the accuracy of a machine learning model. It sums the accuracy and the recall scores of a model. The accuracy measure records the number of times, on the entire data, a model has made a correct guess.

$$F1\,Score = 2 * \frac{Recall \text{ X } Precision}{Recall + Precision} * 100 (9)$$

Specificity: It is determined by the number of people who are tested negative of a disease divided by the total of the number of people who are not infected by that disease. This encompasses the negative test takers and the positive test takers that did not have the disease.

$$Specificity = \frac{TN}{(TN + FP)} \quad (10)$$

Sensitivity: Sensitivity is used when referring to tests and instruments because it is an idea of how efficient the test or the instrument is to locate a situation in a person. It is determined by making a comparison between the number of individuals that test positive to a disease and actual number of individuals with that disease.

$$Sensitivity = \frac{TP}{(TP + FN)} \quad (11)$$

mAP: Mean Average Precision (MAP) is a method of quantifying quality and ranking things. It explores the number of related suggestions and their location in the list. MAP at K= get the average precision (AP) at K over all users, or searches and multiply by 100.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k \quad (12)$$

Table.1 Performance Evaluation Table - Classification

ML Model	Accuracy	Precision	Recall	F1_score	Specificity	Sensitivity	Error

Baseline CNN	0.64667	0.68136	0.64518	0.62753	0.42282	0.86755	0.35333
VGG16	0.96500	0.96500	0.96500	0.96500	0.96477	0.96523	0.03500
ResNet50	0.97000	0.97012	0.96995	0.96999	0.96309	0.97682	0.03000
Proposed Model	0.99917	1.00000	0.99834	0.99917	1.00000	0.99834	0.00083

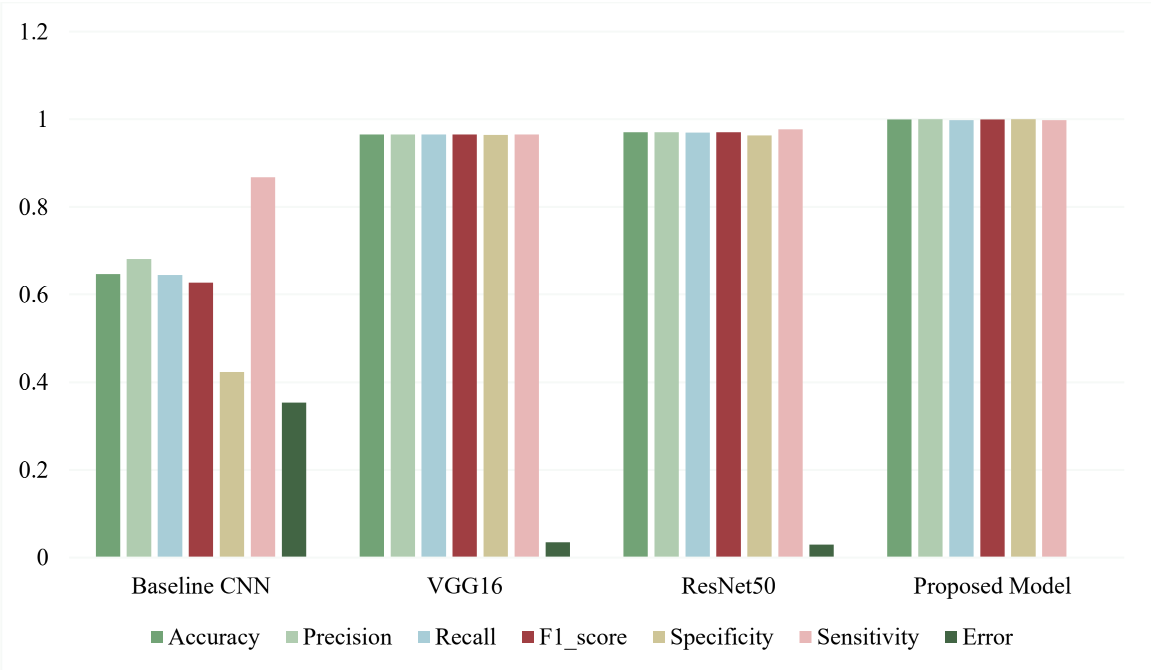
The performance analysis shows that the given model is much better than baseline CNN, VGG16, and ResNet50 in terms of accuracy, sensitivity, and specificity, which are close to 100 percent, balanced, and the lowest error rate, respectively.

Table.2 Performance Evaluation Table - Detection

ML Model	Precision	Recall	mAP
Yolo v5	0.709	0.783	0.787
Yolo v8	0.718	0.749	0.773
Yolo v9	0.703	0.681	0.735
Yolo v11	0.705	0.727	0.750

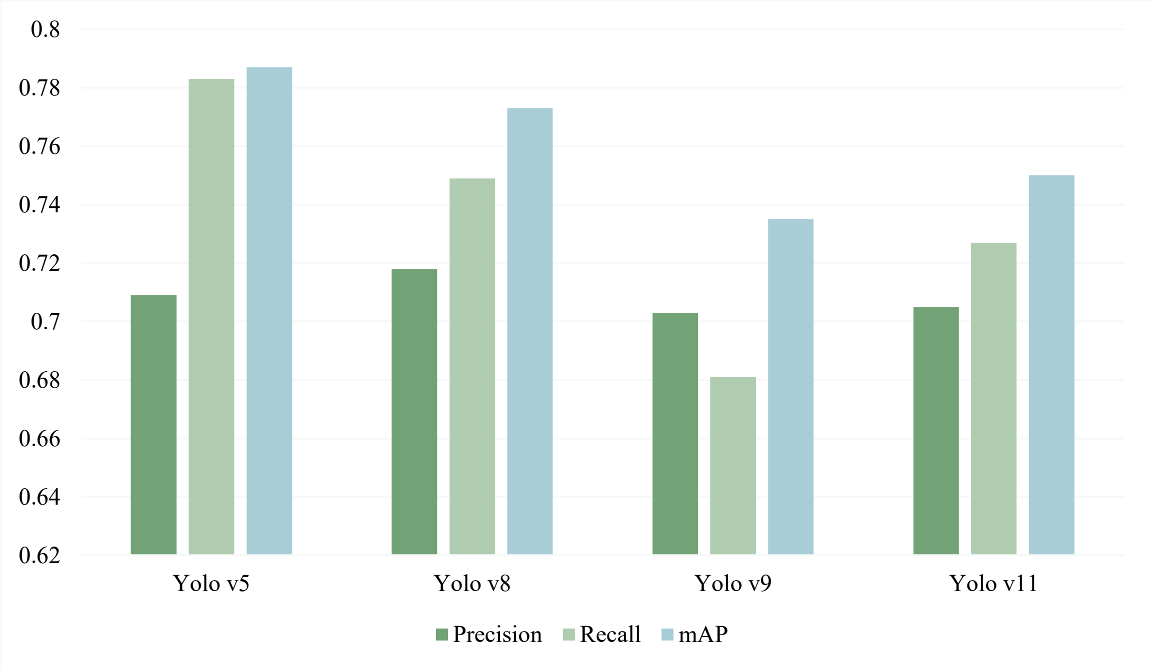
According to object detection, the results of object detection indicate that the mAP and recall of YOLOv5 are the highest, and the accuracy of YOLOv8 is slightly higher. This indicates that the variants of YOLO possess varying strengths and weaknesses in the area of detection.

Graph.1 Comparison Graph



The comparison graph shows that the proposed model regularly does better than CNN, VGG16, and ResNet50 in all evaluation metrics, getting almost perfect results with very little error.

Graph.2 Comparison Graph



As the comparison graph demonstrates, YOLOv5 has the highest recall and mAP, and YOLOv8 has the highest accuracy. This demonstrates that the performance trade-offs of the various versions of YOLO vary.

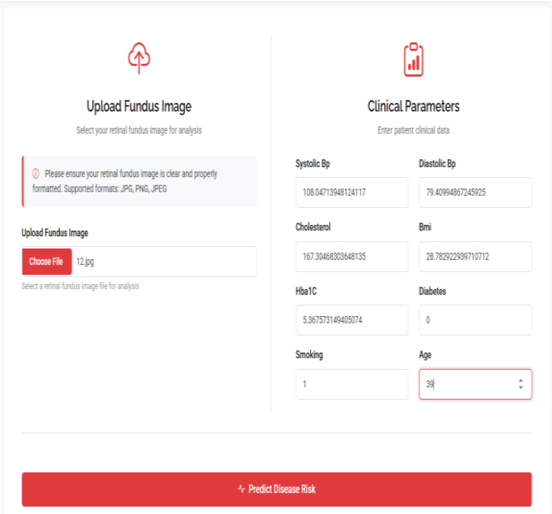


Fig.4 Upload a input image

The interface allows the users to post a picture of the retina fundus and enter clinical details. This enables the disease risks to be predicted accurately using one and simple diagnostic system that incorporates multimodal input.

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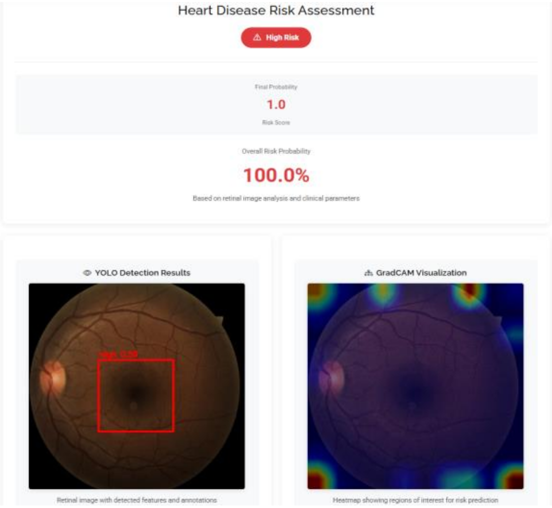

Fig.5 Predicted Result

A high risk of heart disease is sure to be indicated in the output screen. It achieves this by relying on fundus-based YOLO detections and Grad-Cam heatmaps to make the image-based interpretation of what the model relied on to make the final prediction.

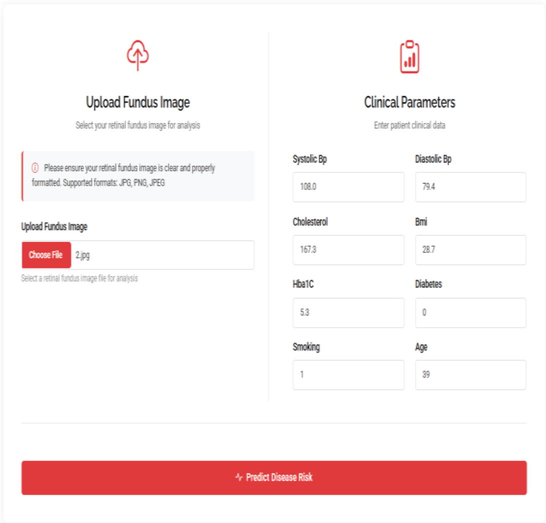

Fig.6 Upload a input image

This input interface helps users to upload a retinal fundus image and add significant clinical parameters. This results in a single multimodal data that may be utilized to precisely forecast the possibility of cardiovascular disease.

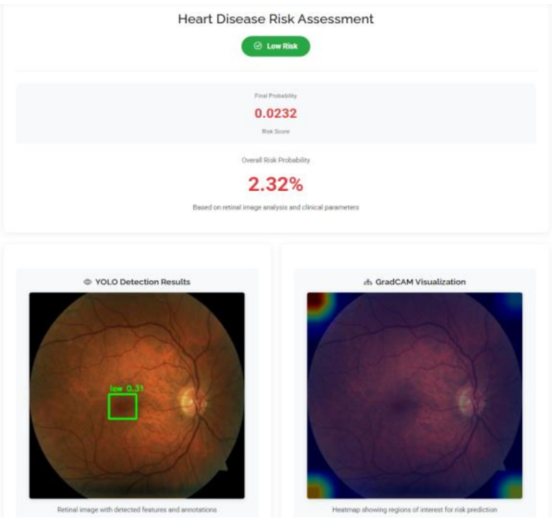

Fig.7 Predicted Result

The outcome indicates that there are low chances of heart disease with 2.32% probability. This is supported by fundus image analysis, YOLO-based features detection, and Grad-CAM visualization that indicates the regions that are the least risky.

5. CONCLUSION

To sum up, the proposed system will help to achieve precise and non-invasive cardiovascular risk evaluation using the retinal fundus imaging. This will contribute to the identification of alterations in the circulatory system that is associated with heart conditions at an early stage. The approach takes the EyePACS data to combine the retinal images and clinical characteristics together to a hybrid learning model. It does so by using the baseline models such as ResNet50 VGG16 and CNN with an EfficientNetV2 feature extractor and 1D CNN layers, which are more efficient in multimodal classification. Object detection was also introduced to assist in locating issues in the retina, and the GradCAM has been applied to facilitate the making of the classification decisions easier to see. The interface is written in Flask and allows you to input the data and view the results in real-time, thus, simplifying the publication. The system was classified with higher accuracy of 99.9% which indicated that it was able to detect tiny patterns of capillary and utilize clinical data to make correct forecasts. These results provide an indication of the strength, accuracy and consistency of the hybrid structure. The new system is an all-inclusive, automated method of determining cardiovascular risk. It simplifies the outcomes, assists physicians in decision-making, and can be applied in the real-world by integrating correct classification, local detection, and user interactive deployment into one platform which is scalable.

Such a system may be enhanced in the future by increasing the number of datasets of other ethnic groups and other eye imaging equipment. This would render the model more general and dependable. Predictions can be even more accurate and assist individuals with various degrees of risk upon the addition of more clinical factors and long-term patient data. The implementation can be extended to the mobile or cloud-based systems to render telemedicine and health monitoring more available to the greater population. The more information about model choices could be provided using advanced AI methods that can be explained, which would assist in trusting and clinical interpretation. Optimization and real-time inference advances will keep on enhancing cardiovascular risk assessment to be more scalable, reliable, and accessible by patients in the real-life healthcare context.

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