



INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

FUNDUS IMAGE CLASSIFICATION USING HYBRID MODEL OF CNN AND R-FCN

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Abstract-

Fundus diseases are the main cause of vision loss. Doctors use special images called fundus images to classify these diseases. Computers can help with classifying using a technology called deep learning. While deep learning techniques like CNN do not effectively remove noise. To overcome the above limitations, we introduce a hybrid model combining CNN and R-FCN. In this model, we pass the fundus images through a Convolutional Neural Network to capture a variety of low-level (edges and textures) and high-level (shapes and patterns) features that are fundamental for identifying diseases in the fundus. It is applied to feature maps developed in CNN and incorporates a mechanism of position-sensitive score map to enhance the detection of regions of interest in the image, such as lesions or vascular abnormalities in retinal images. Further, it enhances the architecture using layers of convolutions for hierarchical features in images followed by a Region Proposal Network, which creates candidate regions for classification. These regions are then classified using a set of fully connected layers, making the system highly capable of localizing and classifying retinal conditions. This innovative approach can detect disease earlier and suggest for best treatment. This paper enhances the accuracy of up to 98% in Fundus image classification.

Keywords: Fundus Images, Retinal Disease Classification, Deep Learning, Region-based Fully Convolutional Networks, Position-Sensitive Score Maps, Diabetic Retinopathy, Glaucoma, Age-related Macular Degeneration, Image Classification, Precision, Recall, F1-Score.

I. Introduction

Fundus imaging is also known as retinal imaging. These are the most essential diagnostic tools in ophthalmology. Retinal images are employed to diagnose and evaluate diseases of the eye, including diabetic retinopathy, glaucoma, age-related macular degeneration (AMD), and retinal vascular diseases. The retina has also been referred to as the window to the brain because of its direct link to the central nervous system, and it is one of the few places where blood vessels may be viewed directly without using invasive techniques. Manual analysis of fundus images by ophthalmologists or trained staff is an important role in clinical practice for the diagnosis and detection of retinal pathology. This is, however, time-consuming, subjective, and highly reliant on the skill of the clinician. Even though some deep learning models, especially Convolutional Neural Networks (CNN), have shown good performance in retinal disease classification, there remain issues with localizing and identifying the areas of interest correctly in fundus images. To solve these problems, this paper suggests a hybrid approach combining CNN and Region-based Fully Convolutional Networks (R-FCN), an advanced object detection technique. The hybrid model would be capable of utilising R-FCN's position-sensitive score map mechanism to improve the localisation of retinal abnormalities, which would improve the classification performance and offer a more efficient, automated retinal disease detection tool.

II. Region based fully convolutional network

Region-based Fully Convolutional Networks (R-FCN) is a more sophisticated version of Fully Convolutional Networks (FCNs) that focuses on optimising the processes of object detection and localisation. Incorporating a Position Sensitive

Score Map and Region Proposal Network (RPN) enhances R-FCN's capabilities beyond the traditional approaches. The network can now recognise the relative position of the object, for instance, retinal lesions or any abnormal features, and classify it. For these reasons, it is arguably the most efficient architecture for classification of retinal diseases from fundus images.

Key Components:

Feature Extraction Layers: Convolutional layers for feature extraction.

Region Proposal Network (RPN): Defines specific candidate regions within the images for further analysis.

Position-Sensitive Score Maps: Assists in the recognition of regions that require a certain defining spatial attribute.

Fully Connected Layers: Used to classify targets in the proposed regions of interest.

III. Datasets

The datasets of fundus images are collected from Kaggle, which are publicly available are used in this paper.



Fig1. sample datasets of seven classes

In the proposed dataset, there are seven types of fundus disease classifications, which are age degeneration laser spots, cataract, diabetic retinopathy, hypertension, myopia, normal, and glaucoma. And here are some sample fundus images of seven classes.

IV. Methodology

In this section, the working process of Fundus image classification using Hybrid model of CNN and R-FCN is discussed.

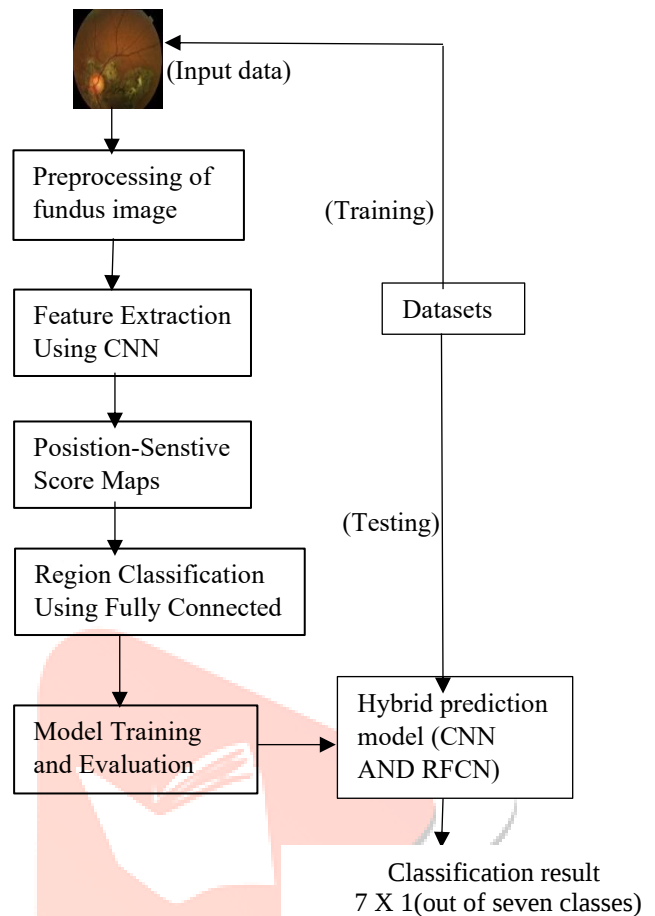


Fig 2. working process of Fundus image classification

Preprocessing of Fundus Images:

At first, Fundus images are resized to 128 x 128 pixels and data augmentation techniques such as rotation, shifting, and scaling are applied to improve the model's robustness.

Feature Extraction Using CNN:

These fundus images go through dedicated layers known as convolutional layers and receive low-level and high-level features such as textures, shapes, and patterns in the eye in the fundus image.

Region Proposal Network (RPN):

RPN applied to feature maps to yield regions of interest (ROIs). Assign objectness scores as well as coordinates of bounding boxes to the proposed regions.

Position-Sensitive Score Maps:

R-FCN employs position-sensitive score maps to detect and identify eye illnesses and gives more attention to small but vital issues (such as lesions and hemorrhages).

Region Classification Using Fully Connected Layers:

Classify the proposed regions into various classes of diseases (such as diabetic retinopathy and glaucoma).

Model Training and Evaluation:

The model was trained using marked fundus images and examine how accurately it performs by using accuracy, precision, recall, and F1-score.

Classification Output:

Finally, this model produces an output in the form of the predicted label of fundus disease, and it can be one of seven types: age degeneration, laser spots, cataract, diabetic retinopathy, hypertension, myopia, normal, and glaucoma.

V. Software and Performance Metrics

MATLAB is a high-level programming and numeric computing platform developed by MathWorks. It is used extensively for technical computing and data analysis. It is particularly powerful in tasks involving matrix operations, linear algebra, and numerical computation. MATLAB is extensively used in many fields, such as engineering, science, finance, and machine learning, in tasks such as algorithm development, data visualisation, signal processing, and simulation. The IDE provided integrates the ease of interface along with in-built libraries and toolboxes suited for various specialised applications, including control systems, image processing, and deep learning. It supports the integration with other programming languages like Python and C++, thereby providing a holistic, collaborative, and multi-disciplinary design space.

The metrics involved in the classification of fundus images using Region-based Fully Convolutional Networks (R-FCN) include accuracy, precision, recall, F1-score, and confusion matrix. Each of these metrics and how they are derived from the output of the trained model are discussed in this section.

Accuracy

Accuracy is the most common measure of classification model assessment. It calculates the overall accuracy of the model to classify all images in the test dataset accurately.

Confusion Matrix

The confusion matrix is a table that helps in visualizing the performance of a classification model. It compares the actual class with the predicted class on a very minute level. The dimensions of the confusion matrix for a multi-class classification problem are $C \times C \times C$, where CC denotes the number of classes. The confusion matrix for each class would show:

Rows: Actual class labels (true labels).

Columns: Predicted class labels.

Precision

Precision is the measure of the correctness of the positive predictions made by the model. Precision is the ratio of true positive predictions, that is, correctly classified instances, to all the positive predictions made by the model.

Recall

Recall, also known as Sensitivity or True Positive Rate, is the ratio of true positive predictions to all actual positive instances.

F1-Score

The F1 score is thereby defined as the harmonic mean of precision and recall. It is a balanced measure where equal

consideration is given to precision and recall with respect to their trade-offs.

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Where:

True Positives (TP): Correctly predicted instances for each class.

False Positives (FP): Instances where the model predicted a class, but the true label was different.

False Negatives (FN): Instances where the model failed to predict the correct class.

True Negatives (TN): Instances where the model correctly identified the absence of a class.

Training the model

This training model shows that each of the metrics gives insight into how well the model performs, both overall and for individual classes, allowing you to identify areas for improvement or potential weakness in the model.

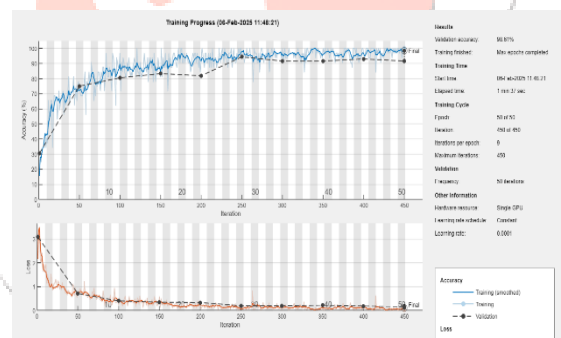


Fig 3a. Training process

		Confusion Matrix						
True Class	Age Degeneration Laser Spots	8						
	Cataract		9					
	Diabetic Retinopathy		1	7				
	Hypertension				22			
	Myopia					5		
	Normal						15	
	Possible glaucoma							5
		Age Degeneration Laser Spots	Cataract	Diabetic Retinopathy	Hypertension	Myopia	Normal	Possible glaucoma
		Predicted Class						

Fig 3b. confusion matrix

Test Accuracy: 98.61%

Performance Metrics:					
Class	Precision	Recall	F1-Score		
Age Degeneration Laser Spots			1.00	1.00	1.00
Cataract	0.90	1.00	0.95		
Diabetic Retinopathy		1.00	0.88	0.93	
Hypertension	1.00		1.00	1.00	
Myopia	1.00	1.00	1.00		
Normal	1.00	1.00	1.00		
Possible glaucoma		1.00	1.00	1.00	

Fig 3c. Training results

Training progress in Fig. 3a. shows an accuracy of 98.61%. Confusion matrix fig. 3b, which displays actual and predicted labels. Diagonal elements represent correctly classified images, and off-diagonal elements represent misclassified images.

In Fig 3c, which shows that overall accuracy of training and probable values of precision, recall and F1-score of each and every class (Age degeneration laser spots, Cataract, Diabetic Retinopathy, Hypertension, Myopia, Normal and Possible glaucoma).

VI. RESULTS

Testing the model

This model provides a comprehensive evaluation of its performance in classifying fundus images. When the images for test are given to the model, it classified and labelled the diagnostic report out of seven possible classes of training.

Predicted Label: Myopia



Fig. 4a prediction of myopia class



Fig. 4b prediction of glaucoma class

Fig. 4a shows that predicted label as myopia and Fig 4b. shows that predicted label as glaucoma out of seven classes.

VII. CONCLUSION

In conclusion, the application of region-based fully convolutional networks for classification of fundus images offers the possibility of more powerful early diagnosis and detection of retinal diseases. This feature is very effectively identified in a fundus image by region proposals and position-sensitive score maps in the model with significant improvements to the classification accuracy, with this current implementation, promising results are received; yet, there is much scope for refinement in the model architecture and data augmentation techniques along with the optimisation strategy, so it should be fully state-of-the-art and robust on

different kinds of datasets. The hybrid model, coupled with other modalities of medical imaging along with real-time applications and appropriate efforts for its extension towards an interpretable model, will find its way towards progressing automated medical diagnosis systems. The future potential of the hybrid model in healthcare, especially in ophthalmology, is immense and will surely continue to contribute toward improving patient outcomes by diagnosing at the right time with accuracy.

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