Detection of Diabetic Retinopathy in Retinal Fundus Image Using YOLO-RF Model

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2021 Sixth International Conference on Image Information Processing (ICIIP) | 978-1-6654-3361-7/21/$31.00 ©2021 IEEE | DOI: 10.1109/ICIIP53038.2021.9702677

Abstract— **Diabetic Retinopathy (DR) is one of the complications of diabetes that impacts blood vessels of a retina because of increased blood sugar. So, it's better to detect and treat at the initial stage. The biggest challenges are inadequate technology assistance for ophthalmologists and difficulty in the manual identification process. These issues can be addressed by technological advancement in the field of Artificial Intelligence for automizing the identification and detection process. An automatic detection helps to identify different stages of DR and helps ophthalmologists to provide treatment according to the stages in order to avoid vision loss. In this paper, proposed system aims to detect the various stages of DR that allows ophthalmologists to identify the DR at its different stage. The proposed system classifies the image data into defined classes using YOLO-RF. The proposed system compared with various traditional machine learning classifiers such as SVM, Decision Tree (DT), Random Forest (RF) and DL model such as YOLO. We have used data from the retinal fundus images of KAGGLE and IDRID. The result showed that proposed system YOLO-RF model performed with good accuracy of 99.3%, precision score of 97.2 and Recall of 99.1.**

Keywords — ***Diabetic retinopathy, NPDR, PDR and Yolo-RF***

I. INTRODUCTION

Diabetic retinopathy [1] is a persistent eye disease which is caused due to high blood sugar. It results in damage to blood vessels in the retina. The vessels can bleed, broaden and have insufficient blood flow. Henceforth, irregular blood vessels grow in the retina resulting in blindness. In its early stage, Diabetic retinopathy exhibits no signs or has slighter vision problems. Eventually this leads to loss of eye vision. An appropriate treatments need to be given to prevent patients from losing sight. Diabetic retinopathy has the subsequent indications: glare vision, deficient eyesight, fluctuating vision, dark and blank areas in vision. Diabetics should see an optician on a regular basis. An optician checks out diabetic retinopathy by imaging the retina with a fundus camera. Accordingly, affected people can be treated and prevented from the vision failure.

A. Diabetic retinopathy stages

Diabetic eye illnesses take several forms. Currently there are two forms of diabetic retinopathy.

Non-Proliferative Diabetic retinopathy [NPDR][2] is a starting stage complication. In NPDR, the insignificant blood vessels in the retina increase in size because of leakage that could result in vision failure. Microaneurysms (MAs), haemorrhages and exudates are some of the detectable NDPR. The sub levels of NPDR are Mild, Moderate and Severe.

Proliferative Diabetic retinopathy [PDR] is the major level of the DR illnesses. It occurs while unusual blood vessel develops inside the retina. This unusual blood vessel can bleed sometimes. When less blood is leaking in the vessels, we feel dark Floaters. If there is more blood loss in the blood vessels of the retina, it can lead to loss of eye vision. Figure 1 shows different stages of diabetic retinopathy.

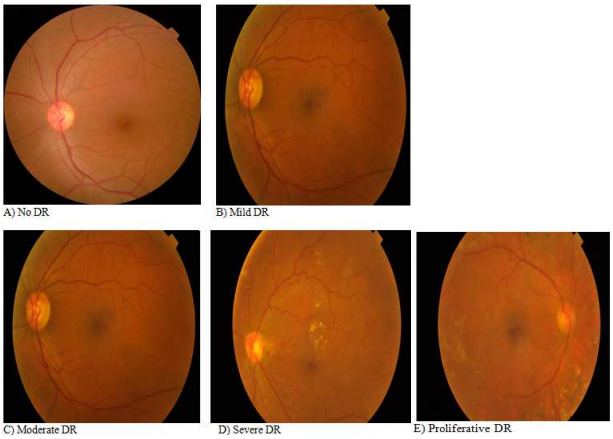

Figure 1 various stages of DR

Presently, the detection and classification of DR is basically accomplished the usage of DL because it has the potential to find the characteristics of the input by fusing numerous sources. The automated system for DR is low-priced, beneficial, work-saving and extra capable in comparison to the human. In our work, the YOLO-RF architecture is used to identify and categorize DR stages for retinal fundus images. The objective is to create an automated system that helps the Doctors to provide precise treatment for the affected people based on the automated DR system result. The paper is prepared as follows. Phase II presents related studies on the classification of DR images. Phase III gives proposed technique implementation. Phase IV presents the results. In the end, Phase V offers the conclusions.

II. LITERATURE SURVEY

In paper [3], provides an identification design with the aid of extracting unique region and quantity of MAs from retinal image. MAs are a preliminary stage of DR and it is vital to discover on a preliminary stage to avoid DR. The paper describes two aspects i.e. detecting the total quantity of MAs as well as region of MAs. The green channel and histogram equalization are considered to preprocess the sample. For the identification of MAs, Contrast limited adaptive histogram equalization, averaging filtering, morphological process and Principal component

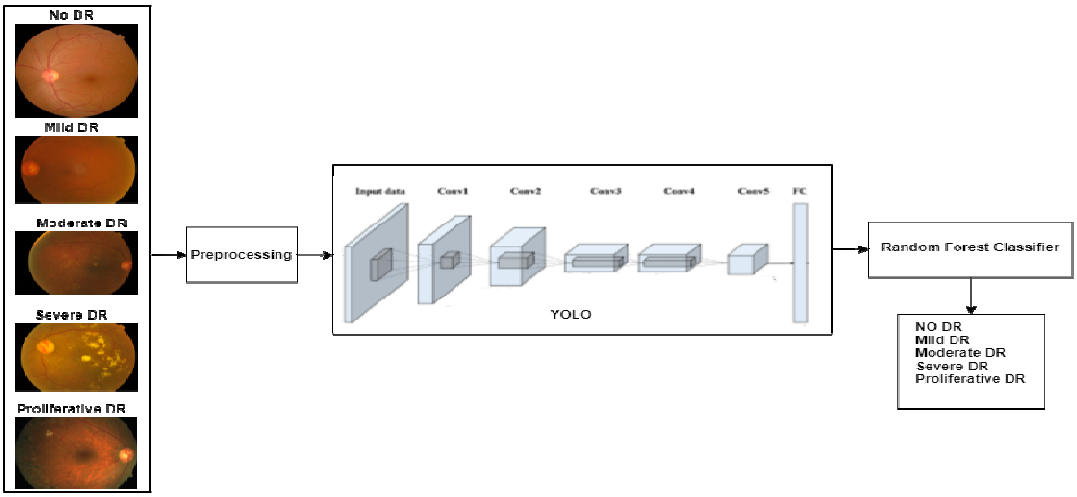

Figure 2 Proposed Architecture

analyses were used. They used SVM technique for the DR categorization. The DR detection method cannot be extended to categorize diabetic retinopathy into more than two categories.

In paper [4], provides effective method, this can find abrasions (exudates, blood vessels and Microaneurysms) among retinal images and intuitively grade the DR disorder. Generally DR abrasions are recognized by means of image processing methods. Features such as blood vessels area, MAs count and exudates area are taken out via the preprocessed images. The knowledge-based fuzzy classifier was used for DR classification.

In paper [5], describes the implementation to determine DR among retinal images. To categorize DR images CNN methods was used. AlexNet, SqueezeNet and VGG-16 CNN models were used for DR classification.

In paper [6], deep convolutional neural network techniques had been used for DR level classification. InceptionNet V3 performed a good result that interprets the ability of using deep CNN for DR image identification.

In paper [7], ResNet, deep CNN networks, had been used for categorizing DR as normal and abnormal for retinal images. This method had been used for retinal fundus images, accessable on the Kaggle site and had obtained results of 85% accuracy and 86% sensitivity.

III. IMPLEMENTATION

In our work, we aim at identification of DR stages. Furthermore the intensity of the DR is viewed as a multi classification problem representing levels of DR such as No DR, Mild DR, Moderate DR, Severe DR and Proliferative DR.

The proposed work consists of 2 major parts. The primary is annotations and second is YOLO-RF model for classification. The primary part promotes the annotations for DR abrasions to find the required vicinity of the abrasion. The second part of the presented framework constructs a latest type of YOLO-RF model. This module contains 2 sub parts, first part is a YOLO framework and another is RF classification. Figure 2 shows the proposed system architecture. Initially, an input images are transferred to the YOLO model together with the annotation's bounding box.

The YOLO has a gaining knowledge functionality that can mechanically take off features and use them as inputs to a traditional Random Forest classifier to develop an image classification solution. The flowchart of the proposed method has been illustrated in Figure 3.

A. Image collections

The dataset used in this paper has been taken from different sources: KAGGLE [8] and IDRID [9]. The repository provides details about on the severity of the disease diabetic retinopathy, and diabetic macular edema for every image. Therefore it is ideal with the development and determination of image analysis algorithms for the detection of DR.

B. Annotations

The area of DR abrasions for each image is vital to distinguish the disorder location for the further process. In proposed method, the LabelImg tool has been accustomed to create an annotations for the retinal image and draw a bounding box for each image manually. The size of the bounding box along with corresponding class for every object are saved in Yolo text file format which is used later in the training process.

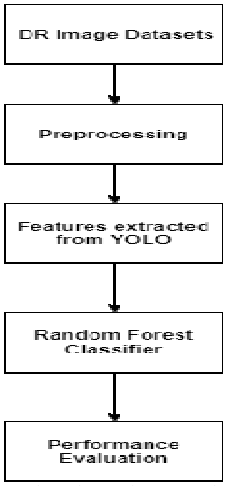

Figure 3 Flowchart of proposed system

C. Data Pre-processing

The purpose of the pre-processing phase is to make use of appropriate image enhancement strategies to obtain the

needed visual quality of the image. Pre-processing carries two methods, image resizing and colour transformation. The retinal fundus images are resized into 227 X 227 and converted resized retinal fundus images into BGR image.

D. Classification

The preprocessed images are fed into YOLO model. YOLO [13] uses CNN to identify and determine varied objects in live. It [14] trains with entire pictures and optimizes the overall performance. The YOLO algorithm works by dividing the preprocessed image into *M* grids, each of which has a uniform dimensional area of AxA. Each *M* grids is responsible for the recognizing and locating the object it contains. Thus, these grids predict the coordinates of bounding box B relative to its cell, along with the object label and the probability that the object being present in the cell. The YOLO has a gaining knowledge functionality that can mechanically take off features. YOLO [15] achieves good accuracy in real time.

The structure of the YOLO network looks like an ordinary CNN, which contains convolutional layers, max pooling layers and a fully connected layer. The Yolo model summary is shown in Figure 4. In fact, classification layer is an ultimate layer of the YOLO framework. In the present study, however, we removed this layer and used the output of the previous layer as features for the classification process. Instead of the final layer, the RF classifier has been used to classify DR images. This approach is specifically designed for image classification of custom datasets. RF is a compound classifier that uses a bootstrap sampling method. The input to random forest technique in the setting of hyper parameters (n_estimators=20, random_state = 42 and max_features=4) together with the training dataset in order to come up with outstanding performance. Hyper parameters are model arguments that are put before the start of the learning process. The YOLO-RF combination system has been used to process DR images. The boon of this model is used to enhance the identification accuracy of different DR levels. The research has performed a high level of accuracy by hyper parameters tuning.

The proposed system YOLO-RF compared with various traditional machine learning classifiers such as SVM, Decision Tree, Random Forest (RF) and DL model such as YOLO.

SVM is a classification method that is very powerful and effective. It is much more efficient to deal with huge datasets of high dimensional data that can hold many features, attributes and characteristics in a distributed and dense format.

DT is of tree shape in which every inner node represents an attribute, every division represents a test result, and every leaf node has a classification result. It can deal with multi-dimensional data.

RF algorithm is a sequence of DT that is ususally trained with a bagging method. It is used to incorporate learning models to improve the overall performance. It only considers a part of the dataset to split nodes. In RF, hyperparameters are used to enhance the predictive capacity of the model.

In SVM, Decision Tree and Random Forest, features are extracted using Morphological [10] and CLAHE [11], [16] techniques. Blood vessels are distributed over the entire surface of the retina. A morphological technique is a processing technique for detecting blood vessels are widely used. In this work the pre-processed image (I_p), morphological opening process is used to localize blood vessels. Opening process technique encompasses erosion that occurs succeeding dilation by the structuring element (SE). The Equation 1 shows opening process:

$$I_{open} = (I_p \ominus SE) \oplus SE \quad (1)$$

Whereas, $\ominus$ stands for erosion,
$\oplus$ stands for dilation.

This process flattens the outline and removes small things in the sample. In order to remove the blood vessels from retinal surface, opening images are subtracted against pre-processed image. Such technique removes the environment and allows only blood vessels to be retained. The threshold is set and applied to obtain binary image.

$$I_{bv} = I_p - I_{open} \quad (2)$$

MAs are elementary level of DR abrasions. It resembles a small red circle pattern and can be recognized on fundus images by its measurement below 125 micrometres. To recognize MA, an image with the green channel is advised. CLAHE is then used as a pre-processing step to obtain a green channel image. Numerous imaging procedures were performed to enhance weak abrasions. When MAs and blood vessels are noticeable, filtering methods are carried out to refine an image condition. Lastly use the threshold to eliminate unnecessary pixels to recognize MAs.

Once, the features are extracted from above mentioned techniques. SVM, RF and Decision Tree algorithms carry various features that the classifier knows about the expected class.

IV. RESULTS

In this paper, we train the classifier via features from YOLO to conduct DR classification by RF classifier. The detection accuracy of the proposed YOLO-RF technique is in contrast with ML models, i.e., SVM, DT, RF, and with DL model i.e., YOLO. Table I show the comparison of the models used in this thesis to classify DR images in terms of accuracy, precision and recalls. Accuracy is a rate of the right estimation to the sum of estimation. Precision specifies the overall performance of the classifier. Recall specifies the ability of the classifier to identify positive instances. Considering the integral of True positives (TP), True negatives (TN), False negatives (FN) and False positives (FP), these measurements are mathematically indicated as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

$$precision = \frac{TP}{TP + FP} \quad (4)$$

$$recall = \frac{TP}{TP + FN} \quad (5)$$

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 227, 227, 96)	34944
activation_1 (Activation)	(None, 227, 227, 96)	0
max_pooling2d_1 (MaxPooling2	(None, 113, 113, 96)	0
conv2d_2 (Conv2D)	(None, 113, 113, 128)	307328
activation_2 (Activation)	(None, 113, 113, 128)	0
max_pooling2d_2 (MaxPooling2	(None, 56, 56, 128)	0
zero_padding2d_1 (ZeroPaddin	(None, 58, 58, 128)	0
conv2d_3 (Conv2D)	(None, 58, 58, 384)	442752
activation_3 (Activation)	(None, 58, 58, 384)	0
zero_padding2d_2 (ZeroPaddin	(None, 60, 60, 384)	0
conv2d_4 (Conv2D)	(None, 60, 60, 192)	663744
activation_4 (Activation)	(None, 60, 60, 192)	0
zero_padding2d_3 (ZeroPaddin	(None, 62, 62, 192)	0
conv2d_5 (Conv2D)	(None, 62, 62, 128)	221312
activation_5 (Activation)	(None, 62, 62, 128)	0
max_pooling2d_3 (MaxPooling2	(None, 31, 31, 128)	0
global_average_pooling2d_1 (	(None, 128)	0
dense_1 (Dense)	(None, 4096)	528384
activation_6 (Activation)	(None, 4096)	0
dropout_1 (Dropout)	(None, 4096)	0
dense_2 (Dense)	(None, 4096)	16781312
activation_7 (Activation)	(None, 4096)	0
dropout_2 (Dropout)	(None, 4096)	0
dense_3 (Dense)	(None, 5)	20485
activation_8 (Activation)	(None, 5)	0

Total params: 19,000,261
Trainable params: 19,000,261
Non-trainable params: 0

Figure 4 model summary

TABLE I: Comparison table of our model with several approaches

Model	Accuracy	Precision	Recall
SVM	46.15	46.15	34.67
Random Forest	30.77	30.77	30.00
Decision Tree	38.46	38.46	30.00
YOLO	98.30	95.30	98.00
YOLO-RF [Proposed]	99.33	97.20	99.10

Our evaluation shows that the classification overall performance of the YOLO-RF is superior to the different methods as shown in Table I. YOLO-RF correctly classifies 99.33% of the images, the classification accuracy of the YOLO, DT, RF and SVM is 98.30%, 38.46%, 30.77% and 46.15%, respectively. Figure 5 exhibits comparison accuracy chart of RF, DT, SVM, Yolo and YOLO-RF. Figure 6 exhibits the comparison precision score of RF, DT, SVM, Yolo and YOLO-RF. Figure 7 exhibits the recall chart of RF, DT, SVM, Yolo and YOLO-RF.

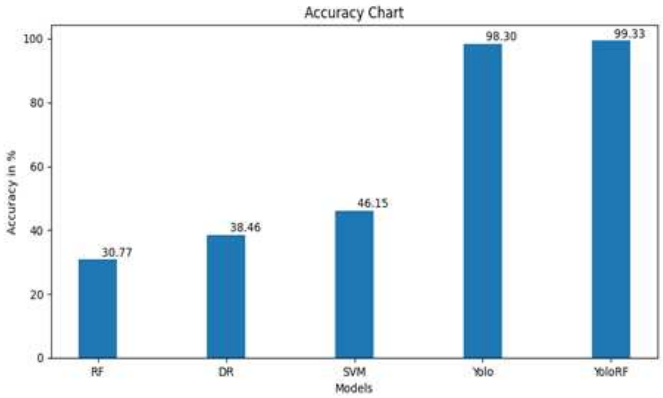

Figure 5 Accuracy chart for RF, DT, SVM, YOLO and YOLO-RF.

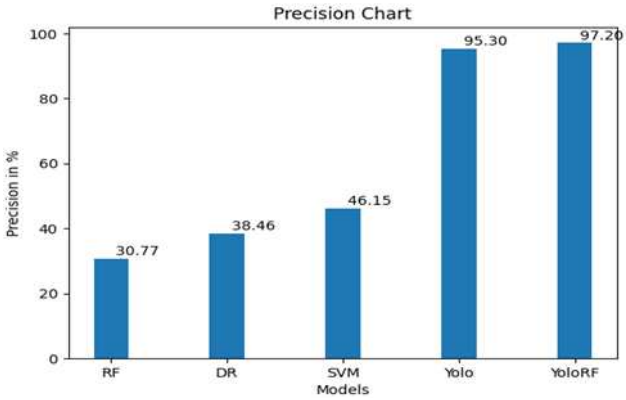

Figure 6 Precision score for RF, DT, SVM, YOLO and YOLO-RF.

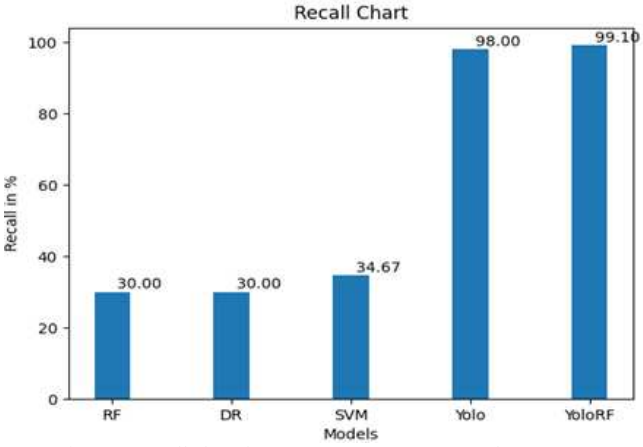

Figure 7 Recall chart for RF, DT, SVM, YOLO and YOLO-RF.

After figuring out the overall performance of the model and verifying it and determining the model accuracy, we finally get the prediction result of the Yolo-RF model, which is the most accurate predictive diabetic retinopathy with an accuracy of 99.33%. The classification of the type of DR is done by loading the image, and then the system predicts the type of DR the affected person has. Thus automatic system helps the doctor to decide and to make the diagnosis based on the classification carried out by the

device. Figure 8 shows that images are recognized based on the severity of DR.

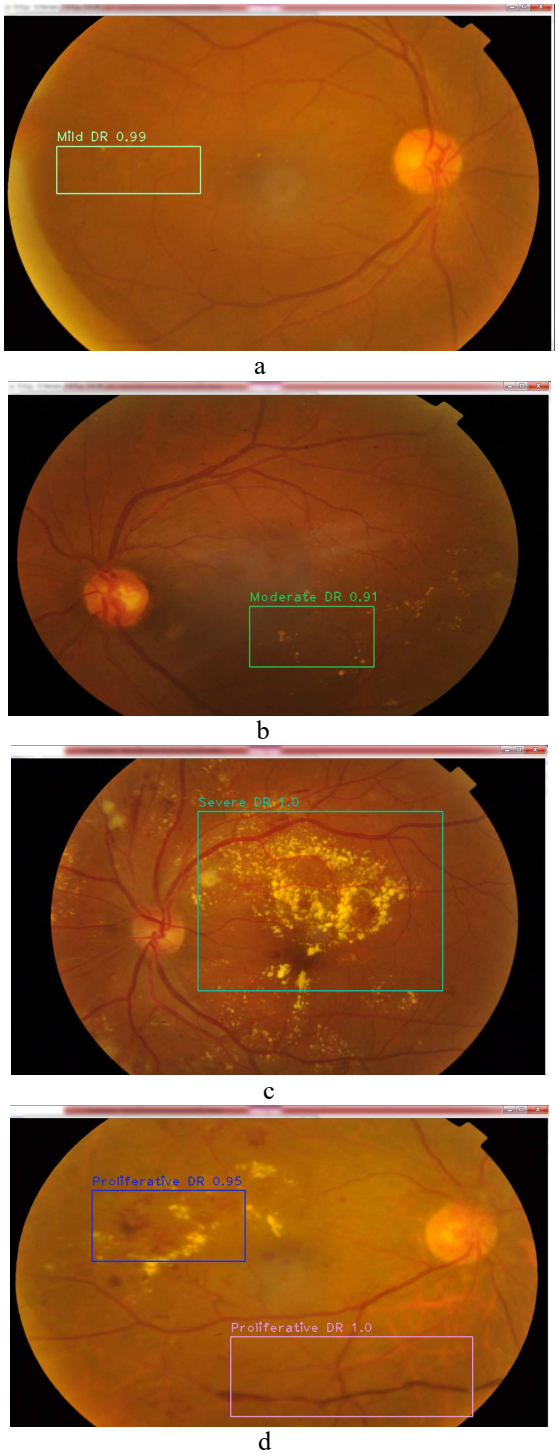

Figure 8 Classification result [a) Mild, b) Moderate, C) Severe and d) Proliferative DR]

V. Conclusion and Future Work

The proposed technique is able to classify the different DR levels on the basis of fundus retinal images and achieves a good accuracy of 99.3% with the YOLO-RF model. The implemented approach enables to categorize the retinal images i.e. No, Mild, Severe, moderate and Proliferative DR. There are numerous detection and categorization methods to categorize DR; In addition, this technique can be strengthened by improving the three-dimensional image recognition of this disease.

Acknowledgments

The author wishes to thank the Faculty of Department of Computer Science at Acharya Institute of technology, Mrs. Naganandhini, Mr. Udhaya Ravishankar, and Mr Dr. Ajith Padyana who greatly helped in the choice of the subject and put the necessary actions and guidelines to complete the research work.

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