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Efficient Detection of Diabetic Retinopathy Using DiaNet

G. Maheshwari[1], B. Rajakumari[2], B. Lakshmidevi [3]

[1]*PG - Dept. of CSE, School of Engineering & Technology, Surya Group of Institutions, Vikravandi, Villupuram.*

[2]*PG - Dept. of CSE, School of Engineering & Technology, Surya Group of Institutions, Vikravandi, villupuram*

[3]*Assistant professor, Dept. of CSE, School of Engineering & Technology, Surya Group of Institutions, Vikravandi villupuram*

ABSTRACT

Diabetes is one of the leading fatal diseases globally, putting a huge burden on the global healthcare system. Early diagnosis of diabetes is hence, of utmost importance and could save many lives. However, current techniques to determine whether a person has diabetes or has the risk of developing diabetes are primarily reliant upon clinical biomarkers. In this article, they propose a novel deep learning architecture to predict if a person has diabetes or not from a photograph of his/her retina.

Keywords — DiaNet, CNN, Mobile net.

INTRODUCTION

Diabetic eye disease (DED) is a group of eye problems that can affect diabetic people. Such disorders include diabetic retinopathy, diabetic macular edema, cataracts, and glaucoma. Diabetes can damage your eyes over time, which can lead to poor vision or even permanent blindness. Early detection of DED symptoms is therefore essential to prevent escalation of the disease and timely treatment. Research difficulties in early detection of DEDs can so far be summarized as follows: changes in the eye anatomy during its early stage are often untraceable by the human eye due to the subtle nature of the features, where large volumes of fundus images put tremendous pressure on scarce specialist resources, making manual analysis practically impossible. Advancements in Artificial Intelligence (AI) offer many advantages to automated DED detection over the manual approach. They include a reduction in human error, time efficiency and detection of minute abnormalities with greater ease. Automated DED detection systems can be assembled through joint image processing techniques using either Machine Learning (ML) or Deep Learning techniques (DL). In DL approaches, images with DED and without DED are collected. Then, the image preprocessing techniques are applied to reduce noise from the images and prepare for the feature extraction process. The pre- processed images are input to DL architecture for the automatic extraction of features and their associated weights to learn the classification rules. The features weights are optimized recursively to ensure the best classification results. Finally, the optimized weights are tested on an unseen set of images. It runs on CPU so it takes more time in computations. Faster R-CNN fixes these issues by introducing a convolutional-based network

i.e. RPN, which reduces proposal time for each image to 10 ms from 2 seconds and improves feature representation by sharing layers with detection

Region Proposal Network (RPN) is an essential component of Faster R- CNN. It is responsible for generating possible regions of interest (region proposals) in images that may contain objects. It uses the concept of attention mechanism in neural networks that instruct the subsequent Fast R-CNN detector where to look for objects in the image. The proposed diagnostic system achieved large data set with an accuracy of 98.5%. proposals. It runs on CPU so it takes more time in computations. Faster R-CNN fixes these issues by introducing a convolutional-based network i.e. RPN, which reduces proposal time for each image to 10 ms from 2 seconds and improves feature representation by sharing layers with detection stages.

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EASE OF USE

First, Significant number of medical pictures are created in a short of time due to advancement in medical imaging and neuroscience. As a result, a strategy for reducing clinical efforts is necessary. Object detection is a technique for recognizing and locating all known items in a given environment. The data from the object detector may be utilized to navigate around any barriers in the area. Automatic tooth detection, pedestrian walking, industrial inspection, quality inspection, traffic analysis, food product inspection, book identification on the shelf, and medical analysis are just a few examples of where object detection is employed. Because human involvement in any endeavor take time. Because humans are more prone to making mistake, the goal of this study topic is to develop a system that can recognize things more precisely

A. **Methodology**

There are various methodologies available for object detection. Some of the techniques are Machine Learning (ML) in which separate rate approaches are required for feature extraction and separate approaches are required for classification, but in deep learning, the same algorithm can be used for feature extraction and classification. And some of The Researches have presented a detailed explanation of some of the deep learning based object detection.

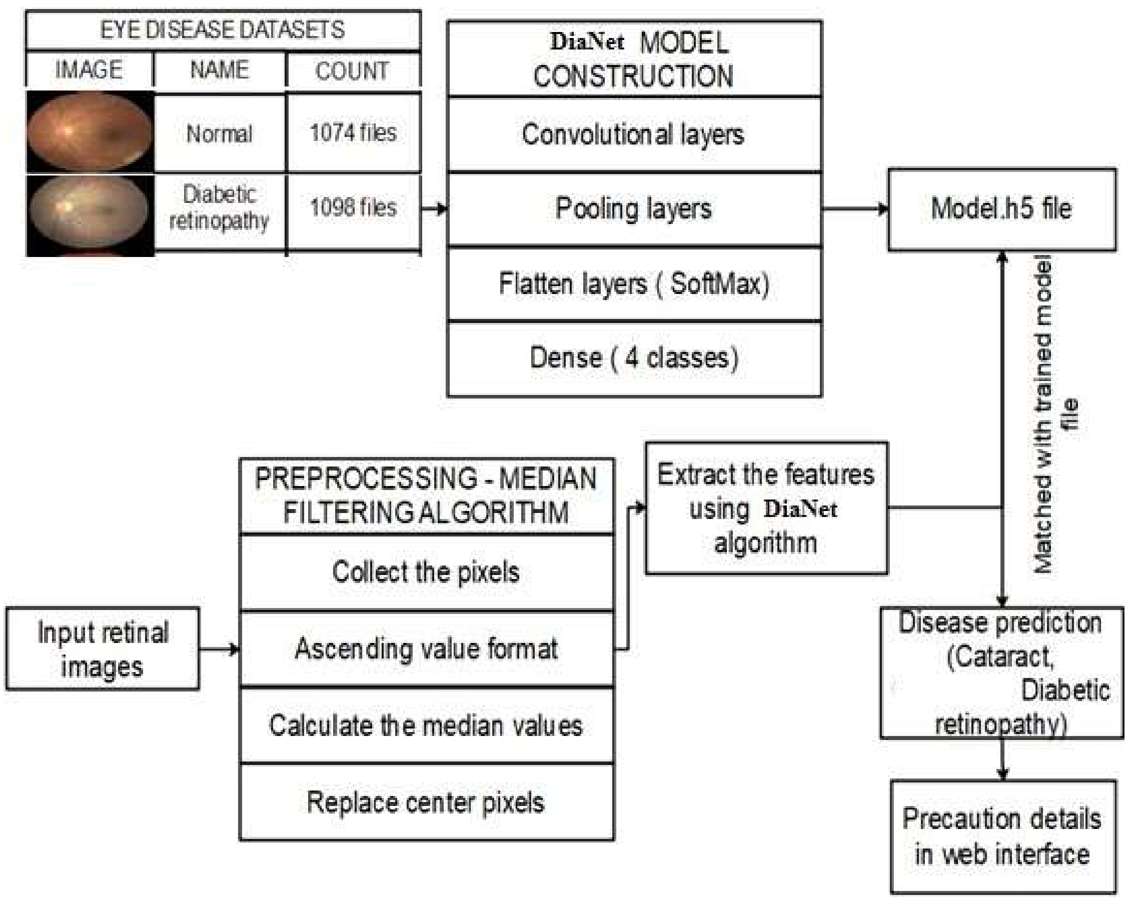

Fig 1: Deep learning neural network

B. R-CNN(Region – based convolutional Neural Network)

A Network named Region – based Convolutional Neural Network The R-CNN pipeline works in such a way that the input image goes through pre-processing until proposals in different regions are generated. Each proposal is resized and passed through the CNN for feature extraction. These features are then used to deduce the object's presence and class of interest from the Support Vector Machines

(SVMs) classifiers. Finally, the bounding box regressor fine- tunes the locations of the objects. Here is the R-CNN architecture delineating how it processes input images for object detection tasks.

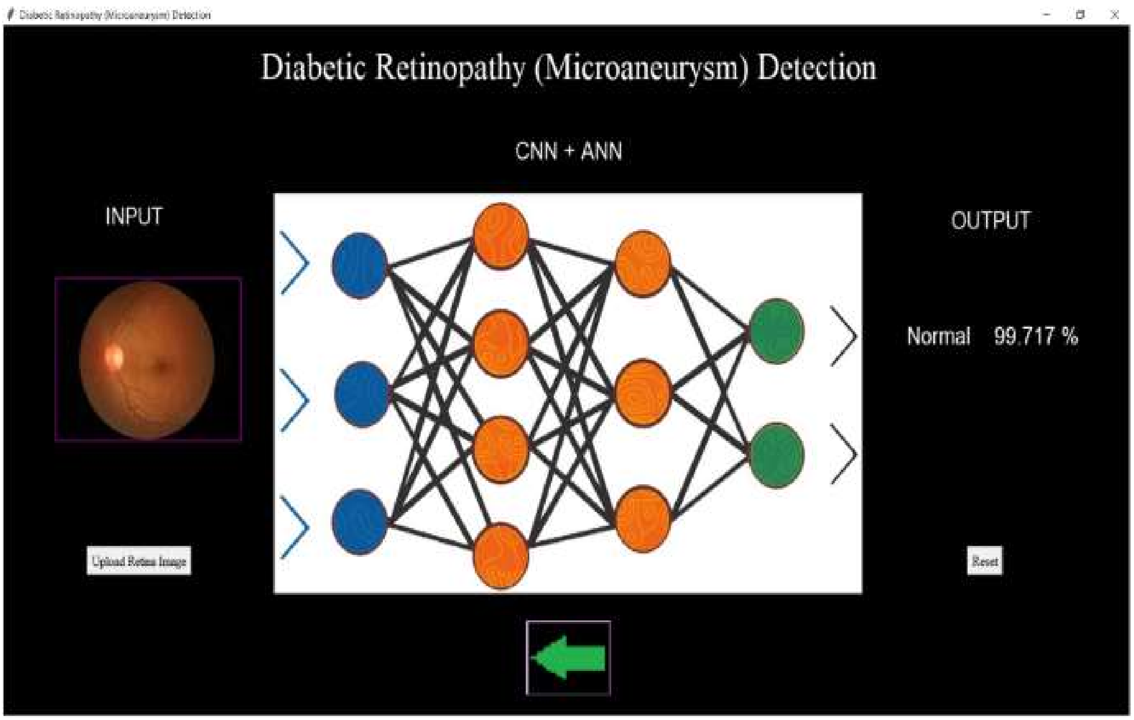

Fig 2: Region Proposal Network Faster R-CNN

depend on three stages:
a.Region proposal
b.Feature extraction
c.Classification

a. Region Proposal:

In Faster R-CNN, a selective – search method is used for region proposal. In this approach, initially the input – image is divided into many regions. Then based on the similarity between CNN regions, the regions are merged. It means it creates a cluster of similar regions. This process is repeated until the object is located. Finally, it established the bounding box on the locate image.

b. Feature extraction:

The cropped portion of the identified region is taken as input to the feature extraction. Then the cropped image is resized to pass through CNN to extract useful features. Here the object is divided into two classes background class and foreground class.

c. Classification:

Here, the input to the classification is feature representation.

A. System Module

Data Collection

System can give training to the data set.

Data – processing

Pre-processing will be done using PCA module

Lession Segmentation

In this step the machine mainly concentrates on the accuracy precision and recall. Without have the

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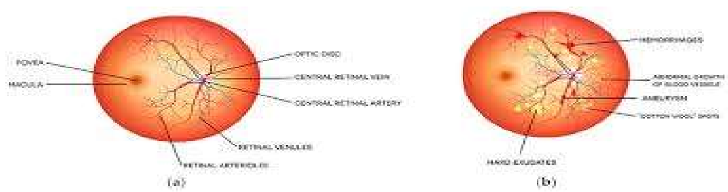
highest rate of accuracy, the development of system is useless. So, it is better to have accuracy system. Accuracy can be calculated by the taking the number of correct predictions from the total number of predictions.



Predictions

B. User Module

1)upload dataset

Then SVM is used for classification purposes, which is used to predict the label of the object is located. The License plate
detection system is proposed using R-CNN. The user uploads the dataset

1) View dataset

The uploaded dataset is viewed by the user.

2) viewing graphs

Graphs can be generated by the system and the user can be view that graphs.

II-ALOGRITHMS

INPUT: Noisy input image

OUTPUT: Enhanced image using 3 * 3 window Steps

1. A 3 * 3 window is slide over the entire image
2. Sort the pixels, denoted by Aij inside the window in ascending order
3. Find the minimum, maximum and median of the pixel values, denoted as Amin Amax and Amed
4. If(Amin < Amax < Amed)
5. Mark the central pixels as uncorrupted(No filtering required)
6. Else
7. If (Amed is not an impulse(Boundary value))
8. Replace a central with Amed Else
9. Replace a central with Ai-1,j

   End if

   End if

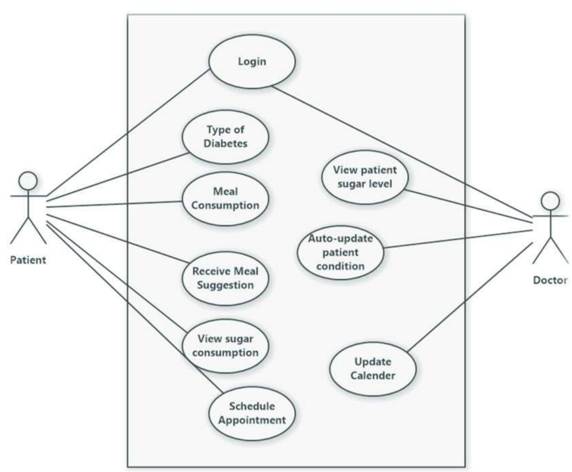


Fig 4: Flowchart

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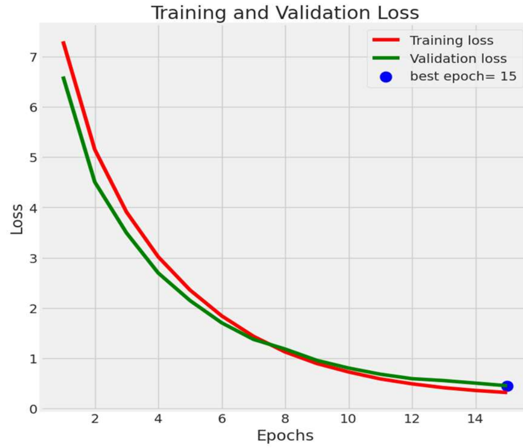

Fig 5: Training Accuracy

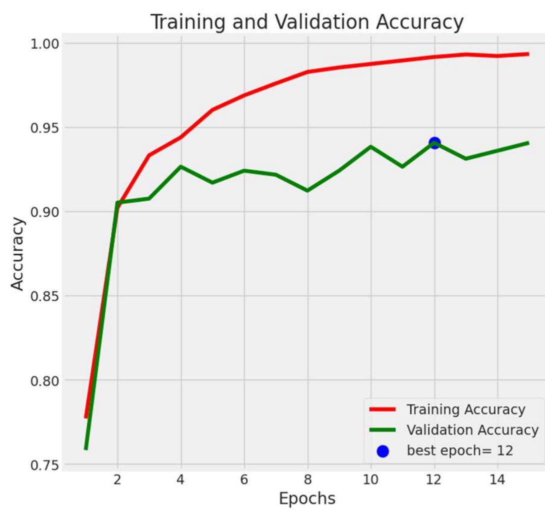

Fig 7: Confusion Matrix

I CONCLUSION

We proposed a data augmentation scheme to compensate for the lack of PDR cases in DR-labeled datasets. It builds upon a heuristic-based algorithm for the generation of neovessel-like structures which relies on the general knowledge of common location and shape of these structures. The synthesized NVs can be introduced in pre-existent retinal images which can then be used for enlarging the datasets for training deep neural.

A. Experimental Result and Analysis

Based on the collected data, automatic lesion detection is implemented using three categories of object detection networks.

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Parameters	Faster R-CNN(VGG-16)	Faster R-CNN(ResNet-101)
Initial learning rate	0.001	0.001
Learning rate strategy	Step	Step
Batch size	16	16
Optimizer	Adam	Adam

Table 1: Comparison of Faster R-CNN and Faster R-CNN

FPN depends on cross-scale connections and weighted feature fusion.

Cross-scale connections: Those nodes are removed with one input edge and no feature fusion. An extra edge is added from original input to an output node to fuse more features. The same layer is repeated multiple times to enable more high level feature fusion.

Weighted feature fusion: Multiple input features are first resized to the same resolution and then sum them up as different input feature are at different resolutions, so they contribute to output feature unequally. For each input, additional weight is added so that network can learn the importance of each input feature

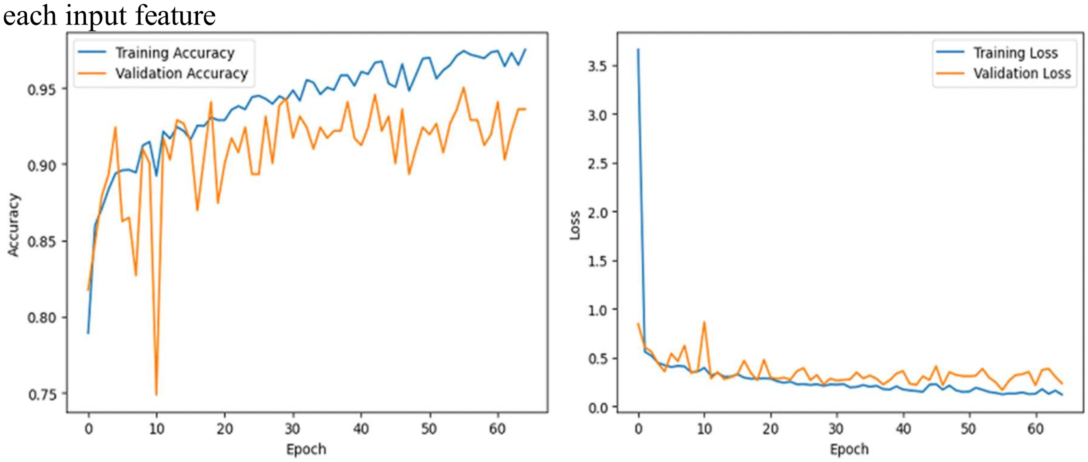

Fig 6: Training Loss

The proposed system effectively classifies diabetic retinopathy stages using a lightweight CNN model with robust image preprocessing. It demonstrates high accuracy despite image variability and noise. This approach holds strong potential for real-world clinical application in early DR detection.

In the proposed design Both MobileNetV2 and DenseNet201 architectures have shown high accuracy in detecting diabetic retinopathy, with accuracy rates of up to 95%.. The proposed architecture MobileNetV2 architecture has been shown to be more efficient in detecting diabetic retinopathy, with a faster processing time compared to DenseNet201. So we need to develop new methods that will help improve the data quality in the future. In the future we will develop these explainable AI methods to help healthcare professionals make more informed decisions based on these AI results.

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