DIAGNOSIS OF DIABETIC RETINOPATHY USING CONVOLUTIONAL NEURAL NETWORKS

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Dissertation submitted in partial fulfillment of the requirements for the degree of

BACHELOR OF TECHNOLOGY

Branch: INFORMATION TECHNOLOGY

Specialization: INFORMATION TECHNOLOGY

of Anna University

October 2020

DEPARTMENT OF INFORMATION TECHNOLOGY

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Bonafide record of work done by

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Dr.S.K.Somasundaram — Faculty guide

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Certified that the candidate was examined in the viva-voce examination held on………………….

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(Internal Examiner) (External Examiner)

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CHAPTER 1

INTRODUCTION

1.1 OBJECTIVE

Diabetic retinopathy is a severe disease that majorly affects patients who are suffering from diabetes. It leads to blindness if left untreated. But the great complexity lies in detecting the disease rather than treating it. Various manual methods have been used by doctors to detect the disease. This results in more consumption of time that leads to a delay in the treatment. Hence the proposed system helps in accurate detection and classification of the disease.

Currently, detecting DR requires a trained clinician to examine and evaluate digital color fundus photographs of the retina. By the time human readers submit their reviews, often a day or two later, the delayed results lead to lost follow up, miscommunication, and delayed treatment.

Clinicians can identify DR by the presence of lesions associated with the vascular abnormalities caused by the disease. While this approach is effective, its resource demands are high. The expertise and equipment required are often lacking in areas where the rate of diabetes in local populations is high and DR detection is most needed. As the number of individuals with diabetes continues to grow, the infrastructure needed to prevent blindness due to DR will become even more insufficient.

The need for a comprehensive and automated method of DR screening has long been recognized, and previous efforts have made good progress using image classification, pattern recognition, and machine learning. With color fundus photography as input, the goal of this project is to develop an automated detection system to the limit of what is possible – ideally resulting in models with realistic clinical potential

1.2 DIABETIC RETINOPATHY

Diabetic retinopathy is one of the major causes of blindness among the people of the world. It is estimated that the disease affects over 95 million people all over the world. This has drastically increased the risk of vision impairment in diabetic patients. The comparison of Normal eye and diseased is shown in Figure 1.

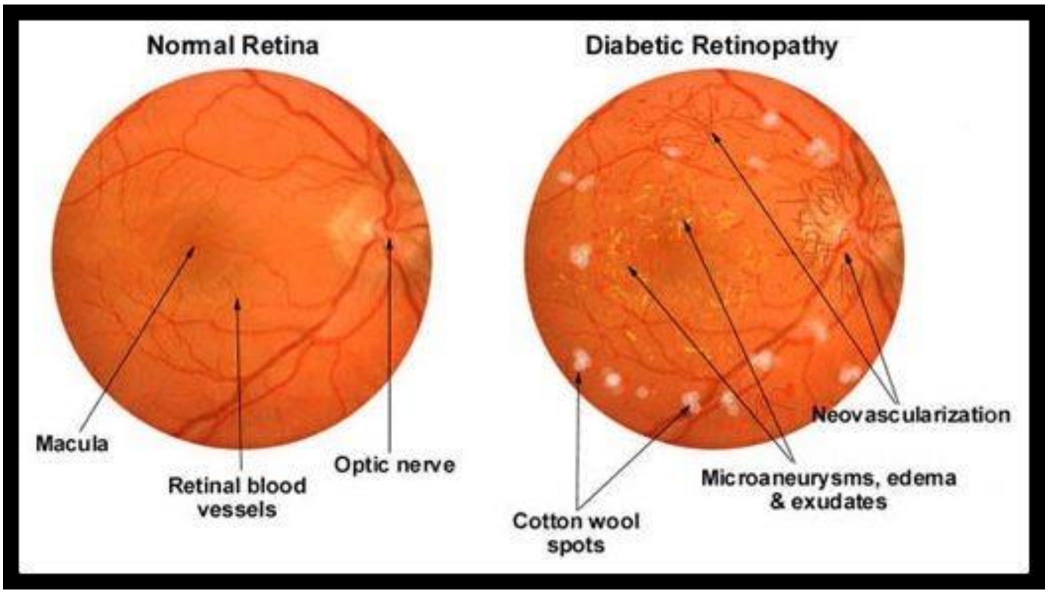


Figure 1 Comparison of Normal eye and Diabetic retinopathy

All diabetics are at risk for developing diabetic retinopathy, but not everyone with diabetes develops it. Diabetes affects blood vessels throughout the body and diabetic retinopathy occurs when blood vessels in the eyes are affected by this process.

The retina lies in the back of the eye and transmits visual images to the brain. When the retinal blood vessels are damaged due to diabetes, they do not function properly. They may leak or bleed, impairing the ability of the retina to detect and transmit images. This is called non-proliferative diabetic retinopathy.

As retinopathy becomes more advanced, new abnormal blood vessels may grow in the retina. This is called proliferative diabetic retinopathy. The abnormal vessels bleed into the eye or cause other problems such as retinal detachment.

PHASES OF DIABETIC RETINOPATHY

Although diabetic retinopathy — caused by chronic high blood sugar — is the most common form of retinopathy, there are several other types. All forms of the disease are associated with damage to the blood vessels in the retina. The stages of diabetic retinopathy are:

1) Mild Non-Proliferative Diabetic Retinopathy (NPDR)

- In this stage, small areas of balloon-like swelling called micro aneurysms form in the retinal blood vessels and may leak fluid into the retina.

2) Moderate NPDR

- As the disease progresses, blood vessels that provide important nourishment to the retina may swell and lose their ability to transport blood.
- During this stage, the appearance of the retina may change as a result of these symptoms. But these changes would only be visible to your eye doctor during a comprehensive eye exam. Untreated moderate NPDR may lead to diabetes.
- Macular edema, or swelling in the macular region of the retina, which can cause serious vision loss.
- Roughly half of all people with DR develop macular edema. Mild and moderate NPDR are sometimes grouped as "early" DR.

3) Severe NPDR

- In this stage, the blood supply to the retina is disrupted, leading to more damage in the blood vessels.

4) Proliferative Diabetic Retinopathy (PDR)

- At this advanced stage of DR, the retina secretes growth factors (substances that stimulate cell growth) to generate new blood vessels.
- These new blood vessels grow along the inside surface of the retina as well as in the vitreous gel, the jelly-like fluid that fills the centre of the eye.
- Because they're fragile, these new blood vessels are more likely to leak and bleed, producing scar tissue that can shrink and lead to retinal detachment the pulling away of the retina from the underlying tissue.

Followed by the introduction of Diabetic Retinopathy, Literature survey and the drawbacks in the existing system are explained briefly. Then the system requirements of the project, problem statement, the project design are mentioned. Followed by that implementation has been reported. Finally conclusion and references have been attached.

CHAPTER 2

LITERATURE SURVEY

2.1 RELATED WORKS

1) An enhanced diabetic retinopathy detection and classification approach using deep convolutional neural network (D. Jude Hemanth, Omer Deperlioglu, Utku Kose) – Published on 1 January 2019. The dataset used is MESSIDOR. The original images are resized to 150x255 and image processing techniques like HE and CLAHE are applied. CNN is used for classification. Here average values for different performance evaluation parameters were obtained as accuracy 97%, sensitivity (recall) 94%,specificity 98%, precision 94%, FScore 94%, and GMean 95%.

2) Deep convolutional neural networks for diabetic retinopathy detection by image classification (Shaohua Wan ,Yan Liang , Yin Zhang) – Published on 3 October 2018. This paper attempts to find an automatic way to classify a given set of fundus images as normal, mild, moderate, severe, proliferative. They used Kaggle dataset. Normalization and data augmentation are adopted to preprocess. The latest deep CNNs like AlexNet, GoogleNet, ResNet, VggNet are coupled with transfer learning and hyper-parameter tuning to achieve good performance. For example, VggNet-s used for classification has acquired accuracy about 95.68%.

3) Automated Detection of Diabetic Retinopathy using Deep Learning (Carson Lam, MD, Darvin Yi, Margaret Guo, and Tony Lindsey) – Published on 2018 May 18. The datasets used are Kaggle and MESSIDOR datasets. The images were normalized and CLAHE is applied. They used CNN algorithm to get accuracy of about 95%. Transfer learning approaches were applied with pretrained AlexNet and GoogleNet architectures from ImageNet.

4) Ramon Pires et al. presented a system that extracts the low-level local features and combines the local features into a mid-level representation feature. Here the local feature extracted from an image can be either sparse or dense. The local feature is transformed into the mid-level extraction BossaNova, which is a representation of the mid-level extraction for image classification. The class-based scheme has two

independent codebooks where one codebook extract descriptors from the lesion present in the retina and another codebook extract descriptors from the healthy retinal image. The cluster is performed only once with the desired codebook size in the class-based scheme and compared with the global dictionary scheme.

5) Li Tang et al. presented an automatic haemorrhage detection from retinal fundus images based on the splat element classification method. The structure of the splats is done in two ways. Calculate the gradients of contrast localization and apply the watershed algorithm to find out the maximum gradients over the scale of interest (SOI). The haemorrhage detection followed by the splat features aggregated the splat feature responses. The splat feature selection based on the filter and wrapper approaches pursued the k-nearest neighbour (KNN) classification.

6) Syna Sreng et al. Proposed an approach to detect the exudates in three stages: pre-processing, OD elimination, and the Exudates extraction. Pre-processing of the fundus image is a major requirement to detect the abnormalities in the retinal image. The RGB colour image changes into a red component for the optic disk discrimination from the blood vessels and the green component for exudates discrimination.

2.2 DRAWBACKS OF THE EXISTING WORKS

Many of them have not considered unhealthy images, high computation time, consideration of small databases, noise effects were not considered, usage of normal segmentation procedures followed, SNR was not considered, etc. A no. of these disadvantages were taken into custody in our exploration work with various parametric information & new algorithms will be created which will be checked through successful Matlab/LabVIEW simulating results done using computer algorithms or maybe thought of doing a hardware implementation of the same.

CHAPTER 3

SYSTEM REQUIREMENTS

3.1 REQUIREMENTS

SOFTWARE REQUIREMENTS	package NumPy package cv2 package Keras package PIL package TensorFlow package os module
MINIMAL HARDWARE REQUIREMENTS	**CPU**-2 x 1.8GHz 32-bit (x86) **RAM**-4 GB Free system disc space-4GB
LANGUAGE USED	Python
PLATFORM USED	Anaconda (Spyder),Google colab
OPERATING SYSTEM USED	Windows 10

3.2 SOFTWARE REQUIREMENTS

3.2.1 NUMPY

NumPy is the fundamental package for scientific computing with Python. It contains a powerful N-dimensional array object sophisticated (broadcasting) functions tools for integrating C/C++ and Fortran code useful linear algebra, Fourier transforms, and random number capabilities. Besides its obvious scientific uses, NumPy can also be used as an efficient multi-dimensional container of generic data. Arbitrary data- types can bedefined. This allows NumPy to seamlessly and speedily integrate with a wide variety of databases. NumPy is licensed under the BSD license, enabling reuse with few restrictions.

3.2.2 CV2

OpenCV is a library of functions aims at real-time computer vision. OpenCV supports a variety of programming languages like Java, C++, Python, etc., It supports different platforms including Windows, Linux, OS X, Android, iOS, etc. OpenCV supports the deep learning frameworks Like TensorFlow and Caffe. OpenCV includes machine learning libraries like boosting, decision tree learning, k-nearest neighbor algorithm, convolution neural network, Naive Bayes classifier, Artificial neural networks, Random forest, Support Vector Machine (SVM), Deep Neural Networks (DNN), etc.,

3.2.3 KERAS

Keras is a high-level neural networks API, capable of running on top of Tensorflow, Theano, and CNTK. It enables fast experimentation through a high level, user-friendly, modular, and extensible API. Keras can also be run on both CPU and GPU. Keras was developed and is maintained by Francois Chollet and is part of the Tensorflow core, which makes it Tensorflows preferred high-level API.

3.2.4 PIL

Python Imaging Library is a free and open-source additional library for the Python programming language that adds support for opening, manipulating, and saving many different image file formats. The Python Imaging Library adds image processing capabilities to your Python interpreter. This library supports many file formats and provides powerful image processing and graphics capabilities.

3.2.5 TENSORFLOW

TensorFlow is an open-source library for numerical computation and large-scale machine learning. TensorFlow bundles together a slew of machine learning and deep learning models and algorithms and makes them useful by way of a common metaphor. It uses Python to provide a convenient front-end API for building applications with the framework while executing those applications in high- performance C++.

TensorFlow can train and run deep neural networks for handwritten digit classification, image recognition, word embedding, recurrent neural networks, sequence-to-sequence models for machine translation, natural language processing, and PDE (partial Differential Equation) based simulations. Best of all, TensorFlow supports production prediction at scale, with the same models used for training.

3.2.7 OS MODULE

The OS module in Python provides functions for interacting with the operating system. OS comes under Python's standard utility modules. This module provides a portable way of using operating system dependent functionality. The *os* and *os.path* modules include many functions to interact with the file system.

3.3 LANGUAGE USED

3.3.1 PYTHON

- Python is a popular programming language.
- It was created by Guido van Rossum, and released in 1991.
- It is used for:
    - web development (server-side)
    - software development
    - mathematics
    - system scripting

3.3.2 FEATURES OF PYTHON

- Python can be used on a server to create web applications.
- Python can be used alongside software to create workflows.
- Python can connect to database systems.
- It can also read and modify files.
- Python can be used to handle big data and perform complex mathematics.
- Python works on different platforms (Windows, Mac, Linux, Raspberry Pi, etc).
- Python is a scripting language.
- Python runs on an interpreter system, meaning that code can be executed as soon as it is written.
- Python has several libraries and packages that can support implementation of image processing, machine learning, deep learning applications.
- Python can be treated procedurally, an object-orientated way, or a functional way.

3.4 PLATFORM USED

3.4.1 ANACONDA

Anaconda Navigator which is included in Anaconda distribution is a desktop graphical user interface (GUI) that helps allow users to launch applications and manage conda packages, environments, and channels without using command-line commands. It helps search for packages on Anaconda Cloud or in a local Anaconda Repository, by installing

them in an environment, running the packages and updating them. It is available for Windows, macOS, and Linux. Anaconda prompt helps install packages.
The open-source packages from the Anaconda repository can be individually installed with the conda install command or using the pip install command that is installed with Anaconda.

3.4.2 GOOGLE COLABORATORY

Google Colaboratory (Colab) is a free online cloud-based Jupyter notebook environment that allows us to train our machine learning and deep learning models on CPUs, GPUs, and TPUs. It is a Google research project created to help disseminate machine learning education and research.
Colab allows you to write and execute Python code in your browser, with

- Zero configuration required
- Free access to GPUs
- Easy sharing

Colab is used extensively in the machine learning community with applications including:

- Developing and training neural networks
- Experimenting with TPUs
- Disseminating AI research

CHAPTER 4

PROBLEM STATEMENT

4.1 PROBLEM DEFINITION

The image processing technology is having its significance for disease detection on medical images. These disease recognition and classification approaches are specific to human organ and image type. One such disease class includes the detection of retinal diseases such as glaucoma detection or diabetic detection. The image processing technique is used for DR feature identification and different algorithms for the detection of diabetic retinopathy.Early detection of this condition is critical for good prognosis.Given an increase in prevalence of both diabetes and associated retinal complications throughout the world, manual methods of diagnosis maybe unable to keep apace with demand for screening service.Hence, an automated solution is of utmost importance.

4.2 NEED FOR THE PROJECT

- It is difficult to identify diabetic retinopathy at the early stage as it often shows few symptoms until its too late to provide effective treatment.
- Clinicians can diagnose diabetic retinopathy by taking photographs of the retina of the patients (retinal fundus images) and check for the abnormalities in the blood vessels.
- Progression to vision impairment can be slowed down or averted if diabetic retinopathy is detected in time.
- As the number of individuals with diabetes continues to grow and patients are needed to undergo eye examinations periodically, the need for an automated system to diagnose this condition is of utmost importance

CHAPTER 5
DESIGN

5.1 PROPOSED SYSTEM

In the proposed methodology, the classification is aimed to be more accurate. It consists of five phases such as data collection, data pre-processing, feature extraction, feature selection, classification, and evaluation metrics to understand the performance.

The block diagram of the proposed methodology is illustrated in the Figure 2.

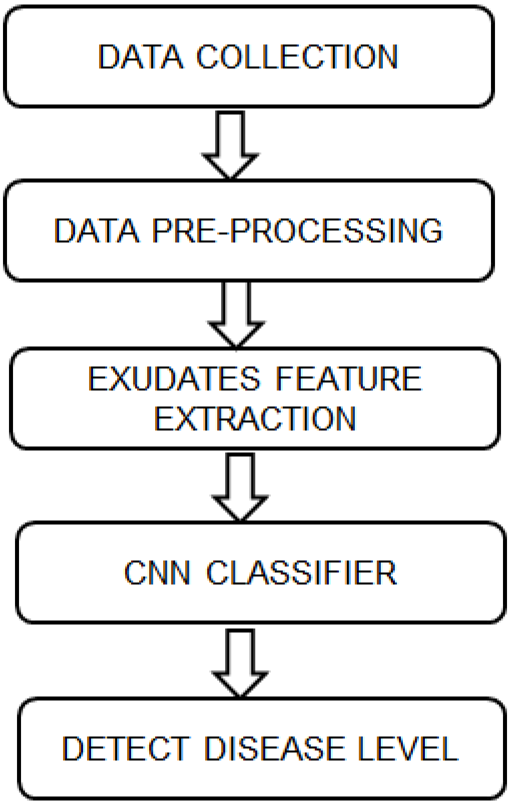


Figure 2 Outline of the proposed system

In this proposed system, a convolutional neural network is used for the classification of diabetic retinopathy. The disease occurs in various stages in diabetic patients with each stage differing in its severity and form.

The various stages of diabetic retinopathy include:

- Mild-NPDR
- Moderate NPDR stage
- Severe NPDR stage
- Proliferative stage

5.2 FLOW OF THE SYSTEM

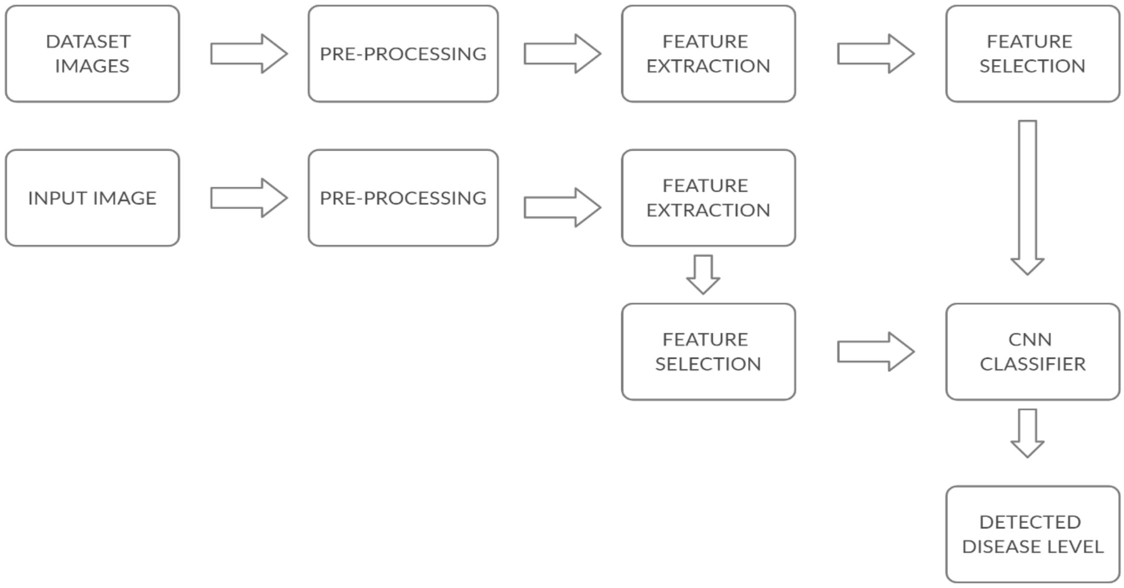


Figure 3 Flow of the system

The entire procedure of developing the model for diabetic retinopathy detection using deep CNN is described further in detail. The complete process is divided into several necessary stages into subsections below, starting with gathering images for the classification process using deep neural networks.

5.2.1 IMAGE ACQUISITION

Image acquisition is the process of capturing the fundus image. The fundus image is captured through a camera with an intricate microscope in the rear of an eye. This image helps in studying the abnormalities in the eye. The image captured is then segmented and classified using a neural network algorithm.

5.2.2 PRE-PROCESSING

The pre-processing steps for exudates extraction are channel extraction, image enhancement, dilation, edge detection with an adaptive threshold value, and noise removal from the image

5.2.3 CLASSIFY AND DETECT DISEASE

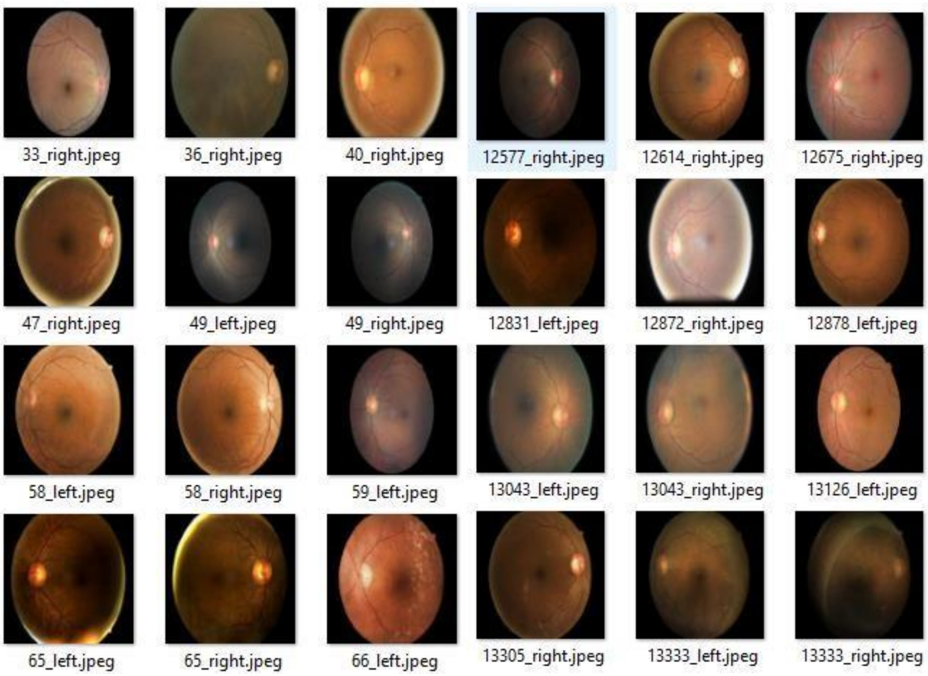
Convolution neural network (CNN) can effectively reduce the spatial dimension of an image without losing important featuresThe classifier for detecting diabetic retinopathy is built using a convolution neural network algorithm. The feature extracted image is feed as input to the classifier; it classifies the image and reports the corresponding level of the disease.

CHAPTER 6

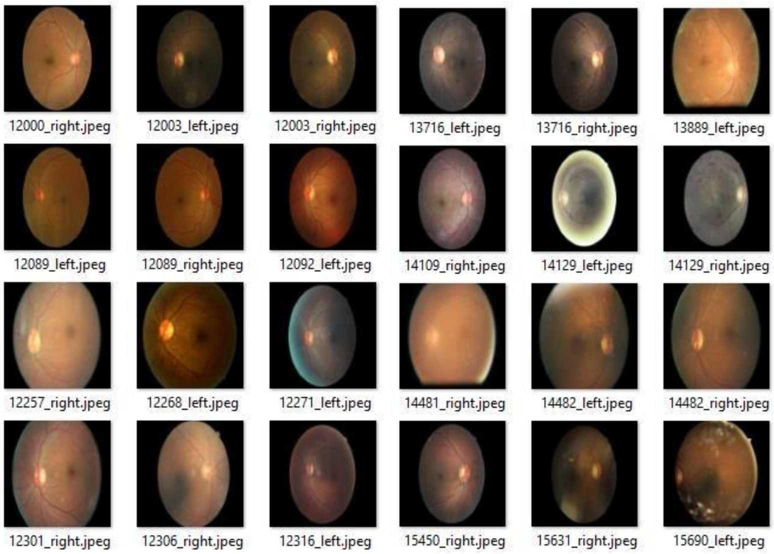
IMPLEMENTATION

6.1 DATASET

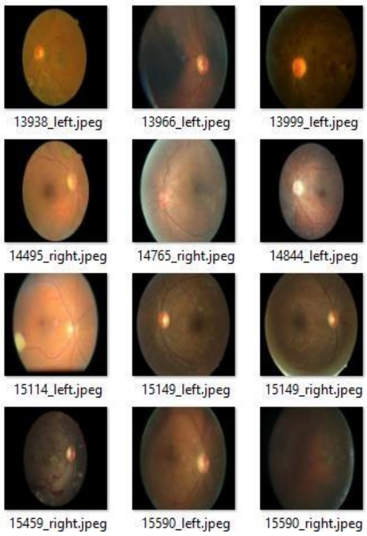
The dataset consists of 35,126 fundus images obtained from Kaggle. 80% of images are taken as train and 20% images as test. The train and test folder contain subfolders of the images grouped based on the severity of the diabetic retinopathy namely Level 0 (No DR), level 1 (Mild DR), level 2 (Moderate DR), level 3 (Severe DR), and level 4 (Proliferate DR) respectively which is shown in Figure 4.



(a) *(b)*



(c) (d)



(e)

Figure 4 Dataset of fundus images representing different levels. (a) – Level 0 (b) – Level 1 (c) – Level 2 (d) – Level 3 (e) – Level 4

6.2 IMAGE PRE-PROCESSING

The first step in training the diabetes detection model is a pre-processing image. The steps for pre-processing are channel extraction, image enhancement, dilation, thresholding, noise removal from the image

6.2.1 CHANNEL EXTRACTION

Dataset image is an RGB colour image, RGB images consist of three channels which are converted to green channel image to make the segmentation process easy. The usage of the blue channel gives a low contrast image and does not contain much information whereas the red channel gives too much noise or it is a saturated image. The green channel is better than the red and blue colour channels.

6.2.2 IMAGE ENHANCEMENT

Image Enhancement is done using Contrast Limited Adaptive Histogram Equalization (CLAHE). CLAHE is applied for contrast enhancement. It operates on small regions in the retinal image and reduces noise. The contrast of each small region is enhanced with a histogram.

6.2.3 DILATION

Dilation is the process of adding pixels to the boundaries of objects in an image, while the erosion process removes pixels on object boundaries. Structuring elements are binary matrix form or a sub-image used to interact with the image. The size and shape of the structuring element used to process the image define the number of pixels to be added or removed from the objects in an image. To extract the exudates in the fundus image the shape of the structuring element used for dilation is elliptical.

6.2.4 THRESHOLD

Thresholding is operation is done to segment the exudates from the fundus image. The source image for thresholding is grayscale. In the source image, if the pixel value of an image is greater than a threshold value, it is assigned as a white region, else it is assigned black region. The thresholding style used for exudates extraction is binary thresholding

6.2.5 NOISE REMOVAL

The median filter replaces a pixel by the median of all pixels in the neighbourhood of a small sliding window. It can filter only outliers and is thus an excellent choice for the removal of especially salt and pepper noise.

The output of each step mentioned is shown in Figure 5.

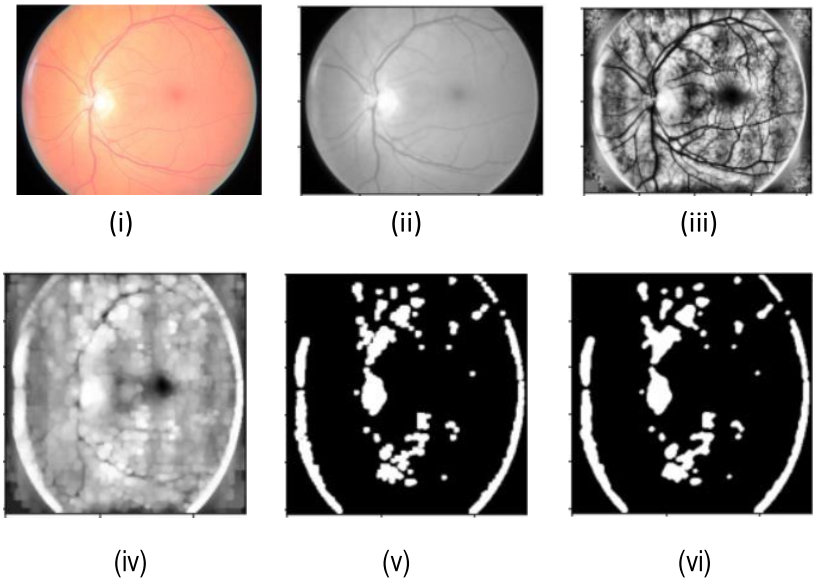


Figure 5 (i) input image (ii) extracting green channel (iii) Applying CLAHE (iv) dilation (v) thresholding (vi) applying Median filter

6.3 NEURAL NETWORK TRAINING

The Convolutional Neural Network algorithm is used to identify diabetic retinopathy. Convolutional Neural Network (CNN) is a Deep Learning algorithm, it takes in an input image assign learnable weights and biases to all features in the image and be able to differentiate one from the other. The CNN applications include Image & Video recognition, human genome mapping projects, Image Analysis & Classification, Automatic Game Playing, Media Recreation, Recommendation Systems, and Natural Language Processing. Different layers and functions of the convolutional neural network used are shown in Figure 6.

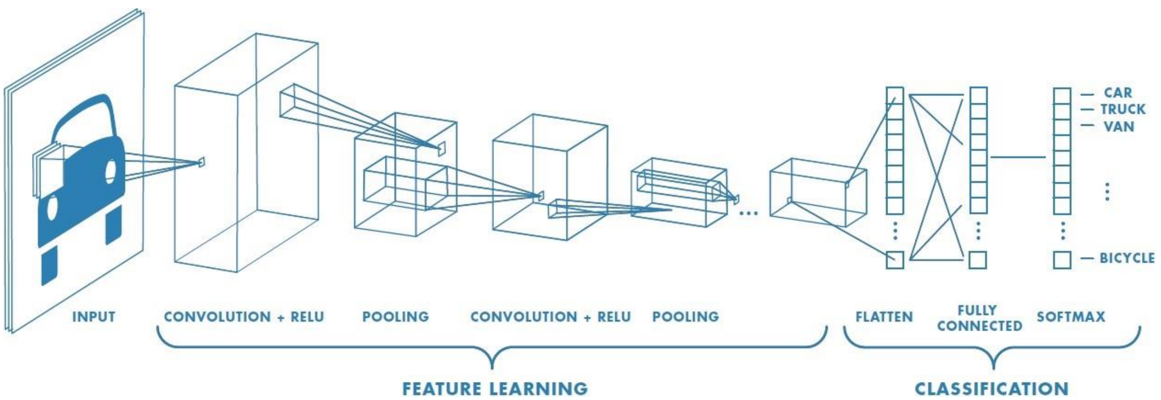


Figure 6 Working of CNN

- **Convolution Layer:** The convolution layer operates on the input image to extract its features. This layer converts the image into a matrix and creates a feature map of the image using the filter or kernel specified. The feature map preserves the spatial features of the input image.

- **Pooling Layer:** Pooling layers responsible to reduce the spatial dimension of the image but retains the important features. Types of pooling are Max pooling and average pooling. Max pooling returns the maximum value in each kernel of the image matrix. Average pooling returns the average of each kernel of the image matrix. Max pooling does Noise Suppressant and also dimensionality reduction but the Average pooling does only dimensionality reduction. So the Max Pooling performs better than Average Pooling. The proposed system uses Max pooling in the neural network.

- **Fully Connected Layer:** The data from the pooling layers are flattened and given as input to the fully connected layer. Flattening helps the fully connected layer to learn the non- linear combination of the input image. This layer outputs the class of the image using the activation function. Between two consecutive fully connected layers activation function and dropout layer are used.

- **Dropout Layer:** The dropout layer reduces the over-fitting of neural networks. It makes the neural network learn robust features.

- **Activation Function:** The activation function learns complex functional mappings between the inputs and response variables by introducing non-linearity. Without the activation function, the neural network cannot learn complex patterns of the data. Some of the activation functions are sigmoid, softmax, tanh, Rectified Linear Units (ReLU), Leaky ReLU, etc. The neural network for detecting the level of diabetic retinopathy uses ReLU in most of the hidden layers and softmax activation function the fully connected layer. The sigmoid activation is not used in a fully connected layer because it can handle only binary classification whereas a softmax activation function handles multi-class classification.

- **Loss Function:** The loss function is used to evaluate the trained model. Some of the loss functions are mean squared error loss, mean squared logarithmic error loss, mean absolute error loss, binary cross-entropy loss, categorical cross-entropy loss, hinge loss, etc. Categorical cross-entropy loss is used in the proposed system because there are more than two output classes.

- **Optimizers:** Optimizers are used to reduce the loss in the model. The optimizers for CNN are Stochastic Gradient Descent (SGD), Root Mean Square Prop (RMSProp), Adaptive Moment Estimation (Adam), Adadelta, adaptive gradient (Adagrad), Adamax, Adadelta, Nadam, and Ftrl. The model for detecting diabetic retinopathy uses Adadelta optimizer.

- **Image Augmentation:** Image augmentation used to increase the size of the dataset images without the need for new images by flipping, shifting, and zooming. Augmentation is necessary because the test images may be flipped, so the neural network should learn these patterns. The augmentation is added only to the training dataset. Keras library provides image augmentation using the ImageDataGenerator class.

TRAINED MODEL:

The trained model is shown in Figure 7.

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_3 (Conv2D)            (None, 254, 254, 16)      448
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 127, 127, 16)      0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 125, 125, 32)      4640
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 62, 62, 32)        0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 60, 60, 64)        18496
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 20, 20, 64)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 20, 20, 64)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 25600)             0
_________________________________________________________________
dense_2 (Dense)              (None, 128)               3276928
_________________________________________________________________
dense_3 (Dense)              (None, 5)                 645
=================================================================
Total params: 3,301,157
Trainable params: 3,301,157
Non-trainable params: 0
_________________________________________________________________
None
Found 28086 images belonging to 5 classes.
Found 7022 images belonging to 5 classes.
```

Figure 7 CNN Trained Model

OUTPUT:

After training the model, new input is taken and tested. The output of the tested image is shown in Figure 8.

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_2 (Conv2D)            (None, 254, 254, 128)     3584
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 252, 252, 128)     147584
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 126, 126, 128)     0
_________________________________________________________________
dropout_2 (Dropout)          (None, 126, 126, 128)     0
_________________________________________________________________
flatten_1 (Flatten)          (None, 2032128)           0
_________________________________________________________________
dense_2 (Dense)              (None, 128)               260112512
_________________________________________________________________
dropout_3 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_3 (Dense)              (None, 5)                 645
=================================================================
Total params: 260,264,325
Trainable params: 260,264,325
Non-trainable params: 0
_________________________________________________________________
None
Level of Diabetic Retinopathy -  level0
```

Figure 8 Tested Output

The dataset images obtained from Kaggle contain 35,126 images. The images are of size 256 x 256 pixels. 80% of images are used for training the convolution neural network model. The model was trained using 8 layers with batch size of 32 and for 25 epochs. It resulted in a training accuracy of 93 %.

6.4 CONFUSION MATRIX:

Confusion matrix helps to evaluate the model's performance. As the name suggests it is a matrix of size n * n where n is the number of class labels.

```
confusion matrix :
[ [25600, 102, 100, 0, 0]
[428, 1414, 457, 100, 39]
[280, 508, 4405, 15, 80]
[10, 28, 156, 541, 137]
[11, 20, 120, 215, 342] ]
```

Figure 9 Confusion matrix

As per our dataset, level 0 class contains 25,802 images. Here our model predicted 25600 correctly but remaining 102 images as level 1, 100 images as level 2. Similarly level 1 contains 2488 images, level 2 contains 5288 images, level 3 contains 872 images and level 4 contains 708 images. The model correctly predicted 1414 images in level 1, 4405 images in level 2, 541 images in level 3 and 342 images in level 4.

6.5 EXPERIMENTAL RESULTS:

A Classification report is used to measure the quality of predictions from a classification algorithm. How many predictions are True and how many are False. More specifically, True Positives, False Positives, True negatives and False Negatives are used to predict the metrics of a classification report. The report shows the main classification metrics precision, recall and f1-score on a per-class basis.

1. **TN / True Negative:** when a case was negative and predicted negative
2. **TP / True Positive:** when a case was positive and predicted positive
3. **FN / False Negative:** when a case was positive but predicted negative
4. **FP / False Positive:** when a case was negative but predicted positive

Precision: Accuracy of positive predictions.

$$Precison = True\ Positives\ /\ (True\ Positives + False\ Positives)$$

Recall: Fraction of positives that were correctly identified.

$$Recall = True\ Positives\ /\ (True\ Positives + False\ Negatives)$$

F1 Score:

$$F1\ Score = 2 \times (Recall \times Precision)\ (Recall + Precision)$$

Using the formulae, the results of precision, recall, f1 – score, support value for our model has been calculated and shown in Figure 9

	precision	recall	f1-score	support
class0	0.94	0.87	0.90	10
class1	0.89	0.90	0.89	10
class2	0.95	0.82	0.88	10
class3	0.88	0.85	0.86	10
class4	0.96	0.79	0.87	10
Avg/Total	0.93	0.85	0.88	50

Figure 10 Experimental Results

The accuracy compared among the algorithms such as Support Vector Machine (SVM), K-means clustering , FMED, OCT is shown in the table below

ALGORITHM	ACCURACY (in %)
FMED	89.4%
Optical Coherence Tomography (OCT)	89%
SVM	86.6%
K-means clustering	92.3%
CNN	93%

We have compared our accuracy among many algorithms and depicted a bar graph which is shown in Figure 10.

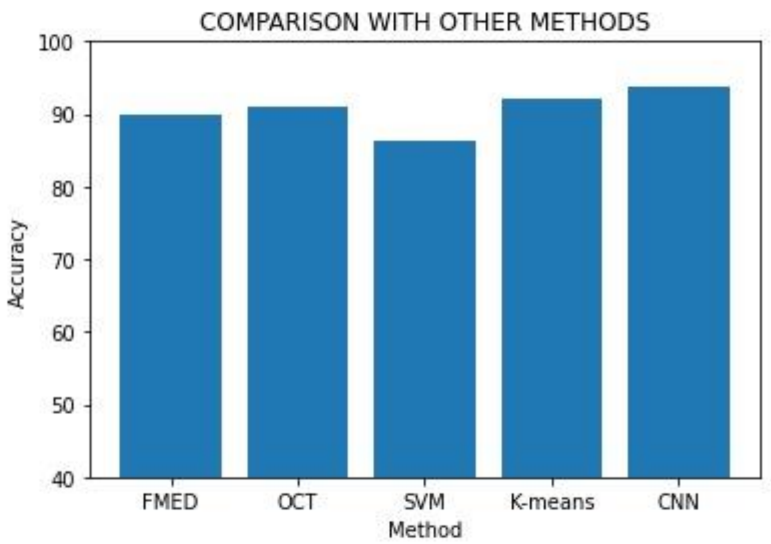


Figure 11 Accuracy comparison chart of various algorithms

CONCLUSION

A system to identify the level of the diabetic retinopathy infection using the deep learning approach is developed. Image processing algorithms are used to extract the exudates feature and then the disease is classified using the Convolutional Neural Network algorithm. The system efficiency can be improved by using more number of training images to train the classifier. The extraction of exudates and other features can be further improved by using clustering techniques. Using CNNs like GoogleNet, AlexNet etc,. and increasing the number of hidden layers can improve the accuracy of the system.

The future scope of the project is to build a complete Convolutional Neural Network Model which extracts features by itself without any external feature extraction techniques (thresholding, clustering etc.).

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