

A HYBRID CONVOLUTIONAL NEURAL NETWORK MODEL FOR AUTOMATIC DIABETIC RETINOPATHY CLASSIFICATION FROM FUNDUS IMAGES

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ABSTRACT

Diabetic Retinopathy (DR) damages eye blood vessels, causing vision issues or blindness if not caught early. Manual detection is slow and error-prone due to complex eye structure. While automated methods exist for identifying DR in images, they struggle with its intricate features, especially in early stages. Progress lies in refining these techniques and collaboration between medical experts and AI researchers. So, We proposes a novel approach to detect diabetic retinopathy using a hybrid convolutional neural network (IR-CNN) model from fundus images. The features extracted from both models such as InceptionV3,and Resnet50 are concatenated and input into the proposed InceptionV3 Resnet50 convolutional neural network (IR-CNN) model for retinopathy classification.. The proposed model is evaluated on a publicly available dataset of fundus images. The experimental results demonstrate that the proposed CNN model achieves higher accuracy, sensitivity, specificity, precision, and f1 score compared to state-of-the-art methods.

1. INTRODUCTION

Diabetic retinopathy is a retinal vascular disorder appears in the diabetic patients. The duration of diabetes is a key factor in the arrival of retinopathy, with the increase in diabetes duration will increase the risk of the DR development. It is also noticed that patients with diabetes usually unaware of the possibility of DR, which leads towards the delayed diagnosis and treatment. Manual detection of DR is time-consuming and requires trained clinical experts to analyze digital color fundus images. However, the delayed outcomes can result in a lack of follow-up and misinformation for patients. Diabetic retinopathy has been manually tested by ophthalmologists until now. Manual diagnosis of DR is time consuming, and therefore, computer-aided diagnosis is gaining attention. These new vessels can bleed in the vitreous, causing dark floaters, and if bleeding is extensive, it can result in blurred vision. Several ML techniques has been developed to detect the DR.

1.1 OBJECTIVE

Diabetes-related retinal diseases, such as diabetic retinopathy (DR), can damage the blood vessels in the eyes, which, if left untreated, is the main cause of vision impairment or blindness. The intricate structure of the eye makes manual detection of diabetic retinopathy laborious and prone to human error.

1.2 PROBLEM STATEMENT

To identify diabetic retinopathy from fundus images, a number of automated methods have been proposed. Unfortunately, especially in the early stages, these methods are not very good at capturing the intricate features that underlie diabetic retinopathy. In this paper, we suggest a novel convolutional neural network (CNN) model-based method for the detection of diabetic retinopathy. Resnet50 and Inceptionv3, two distinct deep learning (DL) models, are used in the proposed model to extract features. These features are then concatenated and fed into the CNN for classification.

1.3 SOFTWARE REQUIREMENTS

Software requirements deal with defining software resource requirements and prerequisites that need to be installed on a computer to provide optimal functioning of an application. These requirements or prerequisites are generally not included in the software installation package and need to be installed separately before the software is installed.

Platform – In computing, a platform describes some sort of framework, either in hardware or software, which allows software to run. Typical platforms include a computer's architecture, operating system, or programming languages and their runtime libraries.

Operating system is one of the first requirements mentioned when defining system requirements (software). Software may not be compatible with different versions of same line of operating systems, although some measure of backward compatibility is often maintained. For example, most software designed for Microsoft Windows XP does not run on Microsoft Windows 98, although the converse is not always true. Similarly, software designed using newer features of Linux Kernel v2.6 generally does not run or compile properly (or at all) on Linux distributions using Kernel v2.2 or v2.4.

APIs and drivers – Software making extensive use of special hardware devices, like high-end display adapters, needs special API or newer device drivers. A good example is DirectX, which is a collection of APIs for handling tasks related to multimedia, especially game programming, on Microsoft platforms.

Web browser – Most web applications and software depending heavily on Internet technologies make use of the default browser installed on system. Microsoft Internet Explorer is a frequent choice of software running on Microsoft Windows, which makes use of ActiveX controls, despite their vulnerabilities.

1) Software : Anaconda

2) Primary Language : Python

3) Frontend Framework : Flask

4) Back-end Framework : Jupyter Notebook

5) Database : Sqlite3

6) Front-End Technologies : HTML, CSS, JavaScript and Bootstrap4

1.4 HARDWARE REQUIREMENTS

The most common set of requirements defined by any operating system or software application is the physical computer resources, also known as hardware. A hardware requirements list is often accompanied by a hardware compatibility list (HCL), especially in case of operating systems. An HCL lists tested, compatible, and sometimes incompatible hardware devices for a particular operating system or application. The following sub-sections discuss the various aspects of hardware requirements.

Architecture – All computer operating systems are designed for a particular computer architecture. Most software applications are limited to particular operating systems running on particular architectures. Although architecture-independent operating systems and applications exist, most need to be recompiled to run on a new architecture. See also a list of common operating systems and their supporting architectures.

Processing power – The power of the central processing unit (CPU) is a fundamental system requirement for any software. Most software running on x86 architecture define processing power as the model and the clock speed of the CPU. Many other features of a CPU that influence its speed and power, like bus speed, cache, and MIPS are often ignored. This definition of power is often erroneous, as AMD Athlon and Intel Pentium CPUs at similar clock speed often have different throughput speeds. Intel Pentium CPUs have enjoyed a considerable degree of popularity, and are often mentioned in this category.

Memory – All software, when run, resides in the random access memory (RAM) of a computer. Memory requirements are defined after considering demands of the application, operating system, supporting software and files, and other running processes. Optimal performance of other unrelated software running on a multi-tasking computer system is also considered when defining this requirement.

Secondary storage – Hard-disk requirements vary, depending on the size of software

installation, temporary files created and maintained while installing or running the software, and possible use of swap space (if RAM is insufficient).

Display adapter – Software requiring a better than average computer graphics display, like graphics editors and high-end games, often define high-end display adapters in the system requirements.

Peripherals – Some software applications need to make extensive and/or special use of some peripherals, demanding the higher performance or functionality of such peripherals. Such peripherals include CD-ROM drives, keyboards, pointing devices, network devices, etc.

1)Operating System : Windows Only

2)Processor : i5 and above

3)Ram : 8gb and above

4)Hard Disk : 25 GB in local drive

2. LITERATURE SURVEY

2.1 Automatic exudates detection from diabetic retinopathy retinal image using fuzzy C-means and morphological methods:

Exudates are the primary signs of diabetic retinopathy which are mainly cause of blindness and could be prevented with an early screening process. Pupil dilation is required in the normal screening process but this affects patients' vision. This paper investigated and proposed automatic methods of exudates detection on low-contrast images taken from non-dilated pupils. The process has two main segmentation steps which are coarse segmentation using Fuzzy C-Means clustering and fine segmentation using morphological reconstruction. Four features, namely intensity, standard deviation on intensity, hue and adapted edge, were selected for coarse segmentation. The detection results are validated by comparing with expert ophthalmologists' hand-drawn ground-truth. The sensitivity and

specificity for our exudates detection are 86% and 99% respectively.

2.2 Automated detection and classification of vascular abnormalities in diabetic retinopathy:

Diabetic retinopathy is a progressive ocular disease. The disease may advance from mild to severe non-proliferative diabetic retinopathy. This paper proposes a method for automated detection and classification of vascular abnormalities in diabetic retinopathy. The vascular abnormalities are detected using scale and orientation selective Gabor filter banks. The proposed method classifies the retinal image as mild or severe case based on the outputs obtained from Gabor filters.

2.3 Automatic grading of retinal vessel caliber:

New clinical studies suggest that narrowing of the retinal blood vessels may be an early indicator of cardiovascular diseases. One measure to quantify the severity of retinal arteriolar narrowing is the arteriolar-to-venular diameter ratio (AVR).

The manual computation of AVR is a tedious process involving repeated measurements of the diameters of all arterioles and venules in the retinal images by human graders. Consistency and reproducibility are concerns. To facilitate large-scale clinical use in the general population, it is essential to have a precise, efficient and automatic system to compute this AVR.

This paper describes a new approach to obtain AVR. The starting points of vessels are detected using a matched Gaussian filter. The detected vessels are traced with the help of a combined Kalman filter and Gaussian filter. A modified Gaussian model that takes into account the central light reflection of arterioles is proposed to describe the vessel profile. The width of a vessel is obtained by data fitting. Experimental results indicate a 97.1% success rate in the identification of vessel starting points, and a 99.2% success rate in the tracking of retinal vessels. The accuracy of the AVR computation is well within the acceptable range of deviation among the human graders, with a mean relative AVR error of 4.4%. The system has interested clinical research groups worldwide and will be tested in clinical studies.

2.4 Validating retinal fundus image analysis algorithms: Issues and a proposal:

This paper concerns the validation of automatic retinal image analysis (ARIA) algorithms. For reasons of space and consistency, we concentrate on the validation of algorithms processing color fundus camera images, currently the largest section of the ARIA literature. We sketch the context (imaging instruments and target tasks) of ARIA validation, summarizing the main image analysis and validation techniques. We then present a list of recommendations focusing on the creation of large repositories of test data created by international consortia, easily accessible via moderated Web sites, including multicenter annotations by multiple experts, specific to clinical tasks, and capable of running submitted software automatically on the data stored, with clear and widely agreed-on performance criteria, to provide a fair comparison.

2.5 Diagnosis of diabetic retinopathy by extracting blood vessels and exudates using retinal color fundus images:

Diabetic retinopathy (DR) is the damage caused by complications of diabetes to the retina. It is one of the leading causes of blindness across the world. Hence, an accurate, premature diagnosis of DR is an essential task because of its potentiality for reducing the number of cases of blindness across the globe. The main objective of our study was to develop a cost-effective computer-aided diagnostic system (CAD) in order to evaluate the performance of the system which automatically classifies images with pathologic features commonly found in DR. This study was performed on 60 South Indian subjects whose age ranged from 50-85 years. For all the subjects, digital images of size 640 x 480 were taken with a CARL ZEISS FF 450 plus Visupac fundus camera. The ground truth results were provided for the presence of pathological conditions such as micro aneurysms, exudates, hemorrhages. An SVM kernel classifier based CAD system was used to report the presence or absence of DR. The next step was the evaluation of the diagnostic capability of the proposed method in order to identify the subjects with DR by means of sensitivity, specificity and accuracy with respect to ground truth results. The proposed system has

attained uppermost classification accuracy, reported so far by means of 5-fold cross validation analysis with the average sensitivity, specificity and accuracy values of 91.6%, 90.5% and 91.2% respectively. In conclusion, our findings suggest that the proposed CAD system would be a useful technique for cataloging the subject with DR.

3. SYSTEM DESIGN

3.1 SYSTEM ARCHITECTURE:

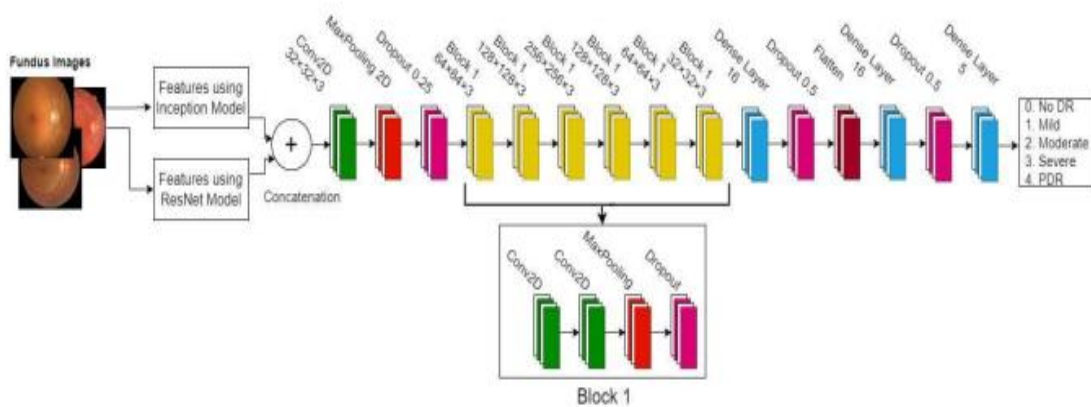
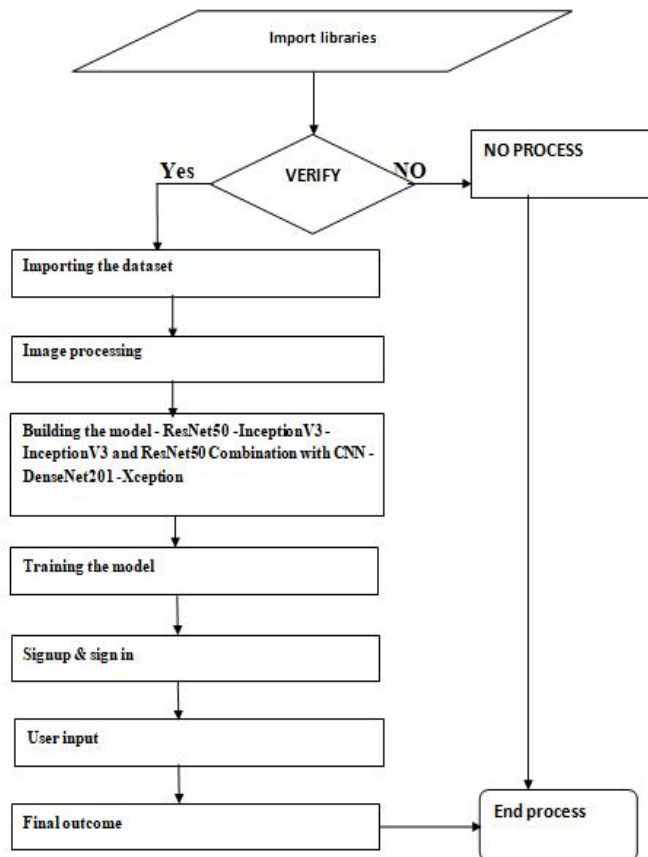


Fig.5.1.1 System architecture

DATA FLOW DIAGRAM:

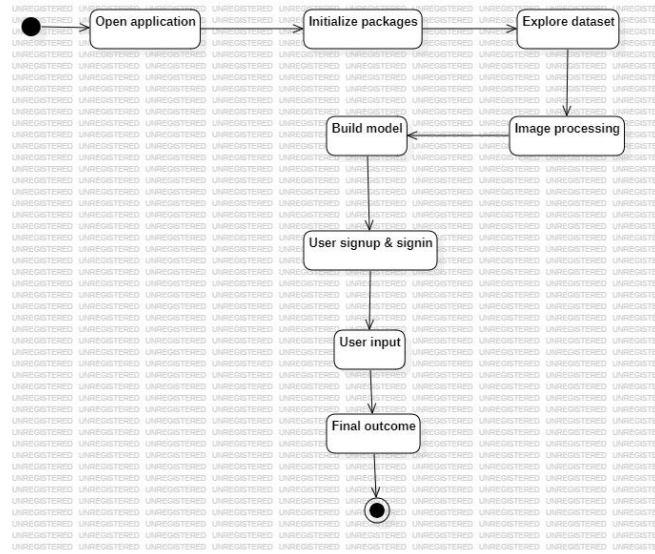
1. The DFD is also called as bubble chart. It is a simple graphical formalism that can be used to represent a system in terms of input data to the system, various processing carried out on this data, and the output data is generated by this system.
2. The data flow diagram (DFD) is one of the most important modeling tools. It is used to model the system components. These components are the system process, the data used by the process, an external entity that interacts with the system and the information flows in the system.
3. DFD shows how the information moves through the system and how it is modified by a series of transformations. It is a graphical technique that depicts information flow and the transformations that are applied as data moves from input to output.

- DFD is also known as bubble chart. A DFD may be used to represent a system at any level of abstraction. DFD may be partitioned into levels that represent increasing information flow and functional detail.



3.2 Activity diagram:

The process flows in the system are captured in the activity diagram. Similar to a state diagram, an activity diagram also consists of activities, actions, transitions, initial and final states, and guard conditions.



4.OUTPUT SCREENS

```
Anaconda Prompt (Anaconda) - python app.py
(base) C:\Users\TruProjects\cd C:\Users\TruProjects\Desktop\15112023\45 - A Hybrid Convolutional Neural Network Model for Automatic Diabetic Retinopathy Classification From Fundus Images\Extension
(base) C:\Users\TruProjects\Desktop\15112023\45 - A Hybrid Convolutional Neural Network Model for Automatic Diabetic Retinopathy Classification From Fundus Images\Extension\python app.py
2023-12-08 17:51:39.301198: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dynamic library 'cudart64_110.dll'; dlerror: cudart64_110.dll not found
2023-12-08 17:51:39.301686: I tensorflow/stream_executor/cuda/cudart_stub.cc:29] Ignore above cudart dlerror if you do not have a GPU set up on your machine.
2023-12-08 17:51:44.961896: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dynamic library 'nvcuda.dll'; dlerror: nvcuda.dll not found
2023-12-08 17:51:44.961241: W tensorflow/stream_executor/cuda/cuda_driver.cc:326] failed call to cuInit: UNKNOWN ERROR (383)
2023-12-08 17:51:44.966006: I tensorflow/stream_executor/cuda/cuda_diagnostics.cc:169] retrieving CUDA diagnostic information for host: DESKTOP-3A1F542
2023-12-08 17:51:44.966244: I tensorflow/stream_executor/cuda/cuda_diagnostics.cc:176] hostname: DESKTOP-3A1F542
2023-12-08 17:51:44.968355: I tensorflow/core/platform/cpu_feature_guard.cc:142] This TensorFlow binary is optimized with oneAPI Deep Neural Network Library (oneDNN) to use the following CPU instructions in performance-critical operations: AVX AVX2
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
* Serving Flask app "app" (lazy loading)
* Environment: production
WARNING: This is a development server. Do not use it in a production deployment.
Use a production WSGI server instead.
* Debug mode: off
* Running on http://127.0.0.1:5000/ (Press CTRL+C to quit)
```

Fig.4.1 Execution of Code

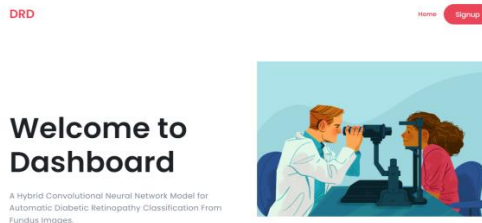


Fig. 4.2 Dashboard

The image shows a 'Sign Up' form on a light blue background. The form is divided into two columns. The left column contains the following fields: 'Username' (with a placeholder 'Username'), 'Name' (with a placeholder 'Name'), 'Email' (with a placeholder 'Email'), 'Mobile' (with a placeholder 'Mobile'), and 'Password' (with a placeholder 'Password' and a visibility toggle). The right column contains a dark blue 'Sign Up' button, the text 'Click here for Signin', and a dark blue 'Signin' button.

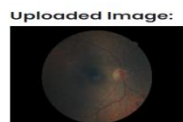
Fig.4.3 sign UP page

The image shows a 'Login Form' on a light blue background. The form is divided into two columns. The left column contains the following fields: 'Sign In' (with a placeholder 'Username'), 'Username' (with a placeholder 'Username'), 'Password' (with a placeholder 'Password' and a visibility toggle), and 'Password' (with a placeholder 'Password' and a visibility toggle). The right column contains a dark blue 'Sign In' button, the text 'Click here for Signin', a dark blue 'Signup' button, the text '— Or Sign In With —', and two social media icons (Facebook and Twitter).

Fig.4.4 Login Page

The image shows a file upload interface. It consists of a 'Choose File' button followed by the text 'No file chosen'. Below this is an 'Upload' button.

Fig.4.5 Upload Image



The Patient is Diagnosis with Normal DR

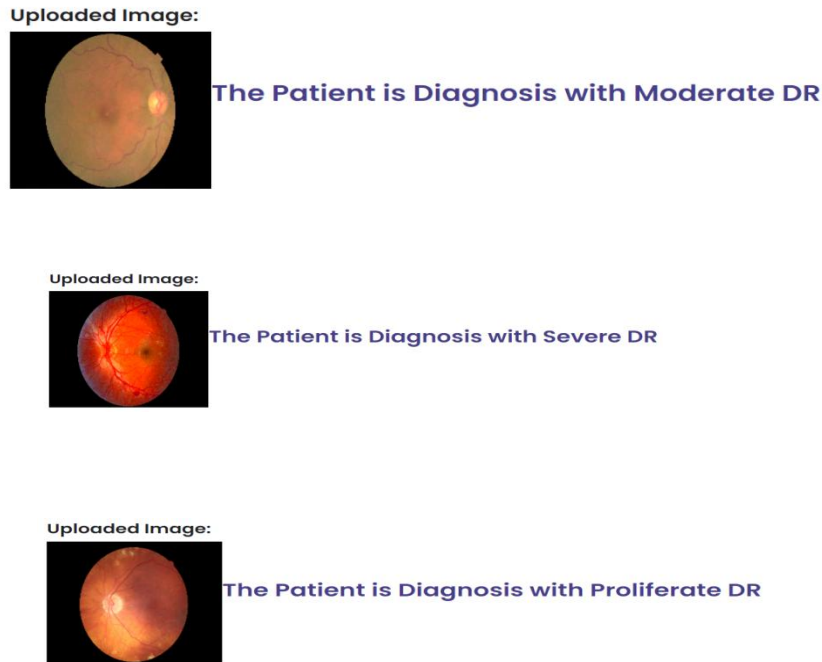


Fig.4.6 Types of DR Classification Result

5. CONCLUSION

We propose a hybrid CNN(IR-CNN) model for automatic diabetic retinopathy classification from fundus images. The proposed approach is an end-to-end mechanism that utilizes Inceptionv3 and Resnet50 for feature extraction of diabetic fundus images. The features extracted from both models are concatenated and input into the proposed InceptionV3 Resnet50 convolutional neural network (IR-CNN) model for retinopathy classification. Different experiments are performed including image enhancement and data augmentation methods to increase the performance of the proposed model. The use of deep learning models, such as Resnet50 and Inceptionv3, for feature extraction enables the model to capture the complex features underlying diabetic retinopathy, leading to more accurate and reliable classification results. Our proposed model achieves higher accuracy,

sensitivity, specificity, precision, and f1 score compared to state-of-the-art methods.

6. FUTURE ENHANCEMENT

- Future research can focus on refining the proposed CNN network to achieve even higher accuracy rates in diabetic retinopathy detection, possibly surpassing current benchmarks.
- Further studies could explore the integration of the developed model into clinical practice, potentially streamlining diagnosis processes and enhancing patient outcomes through early detection and intervention.
- Continued evaluation of the model's robustness across diverse patient demographics and image variations would ensure its reliability in real-world clinical settings.
- Efforts can be directed towards optimizing the computational efficiency of the model and developing user-friendly interfaces, making it accessible and practical for widespread adoption in healthcare facilities.
- Future applications could explore utilizing the CNN network for longitudinal monitoring of diabetic retinopathy progression, facilitating personalized treatment plans and monitoring response to interventions over time.

7. REFERENCE

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