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Early Detection Software for Diabetes Retinopathy

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Abstract. It has been claimed that technology utilized in laboratories does not directly translate to healthcare. Over the last few years, research into the application of Artificial Intelligence (AI) in the diagnosis of Diabetic Retinopathy (DR) has exploded, but little of that information has been translated into practice to aid people in need.One argument is that it is a new area with untested technologies that is changing far too quickly. Furthermore, the Real Healthcare situation can be extremely difficult, posing several challenges ranging from rigorous restrictions to population heterogeneity. A workable solution must meet all of these issues, including ethics, standards, and any security risks. It's also worth noting that existing AI is limited to a few restricted applications and may struggle to grow when faced with problems of varying complexity. A patient with DR, for example, may have other health issues such as glaucoma or cataracts. DR has been a primary cause of blindness for millions of people around the world, and because it is difficult to diagnose when it is treatable, early eye screening is the cure. In this study, we aim to combine Artificial Intelligence with other technologies to provide a low-cost Diabetic Retinopathy diagnosis while also attempting to overcome existing barriers to widespread eye screening adoption

.**Keywords:** Artificial Intelligence, Computer Vision, Image Classification and Auto-detection, Convolutional Neural Networks, Diabetic Retinopathy.

1. Introduction

Every year, Diabetic Retinopathy is the leading cause of blindness in diabetics. Over 285 million individuals are at risk worldwide, and Diabetic Retinopathy (DR) screening necessitates highly trained medical personnel, which are in limited supply. Because DR is largely asymptomatic, it might go unnoticed until late in its progression. It's treatable if caught early [10]. The process of DR diagnosis is time-consuming, difficult to scale, and requires large, expensive equipment that is out of reach for most medical facilities [11].

Artificial Intelligence for Diabetic Retinopathy Diagnosis from Digital Fundus Images has improved dramatically over the last ten years, thanks to breakthroughs in image categorization technology. From accuracies as low as 80% to the now-standard figures of >96%, AI image categorization of DR fundus images now rivals or even exceeds the accuracies of a highly specialized ophthalmologist [12].

Technology utilized in a lab does not directly translate to what we do in healthcare," said IDX Founder and CEO (Google, Verily using AI to screen for diabetic retinopathy in India Healthcare IT News, n.d.). There are a variety of causes behind this. It would be extremely costly and time-consuming to recreate a fully natural environment in which technology development should take place.

Before any further implementations, a proof of concept is required. This has occurred in the case of DR diagnosis utilizing AI, and what remains is technological transfer to benefit the customer. This capstone project aims to solve the different roadblocks to progress by providing a low-cost solution for DR diagnosis to the general public.

The aim of the research is that Diabetic Retinopathy diagnosis could be automated to compensate for the severe shortage of DR eye specialists by reducing the time it takes to diagnose a patient to near real-time. This would allow ophthalmologists to focus on therapy rather than diagnosis, freeing up crucial time. Clinicians could screen more people on a large scale using a modified Smartphone AI-enabled or adaptable device, as suggested by [13] and [14], combined with advanced image processing and classification algorithms running on either a Web App or Desktop environment. This will eventually lead to lower screening costs and the expansion of mass screening campaigns. Many previously undiscovered cases can be identified at an early stage and treated by a medical doctor thanks to these open efforts.

As a result, in this project, we propose using AI to automate diagnosis through a simpler and less expensive setup process, which It will reduce the process and allow comprehensive screening and thus early detection of DR, which also paves the way for early treatment. The proposed system has been analysed, designed, and tested using software development techniques and working in a scientific and systematic manner using software engineering tools in order to arrive at the correct construction of the system. As well as dealing with analysis, design, programming, and entity-oriented testing instead of traditional methods in order to program and build a system to detect diabetic retinopathy to be user-friendly by users and provide service to patients in exchange for a high degree of efficiency.

2. Literature Review

1. Pratt et al. [4] presented a CNN architecture for classifying five phases, but due to the nature of architecture, they were unable to effectively define the moderate stage. Another drawback is that they employed Kaggle's skewed dataset, which resulted in high specificity but low sensitivity.
2. Gondal et al. [1] developed a CNN model for Diabetic Retinopathy that is referable (RDR). They used the Kaggle and DiaretDB1 datasets, with the Kaggle dataset being used for training and DiaretDB1 being used for testing. They employ binary classification, with normal and moderate phases being classified as non-referable DR and the remaining three stages being classified as referable DR. On DiaretDB1, the CNN model's performance is measured using binary classification, which yields a sensitivity of 93.6 percent and a specificity of 97.6 percent.
3. Wang et al. [2] introduced a unique architecture that classifies images as normal/abnormal, referable/non-referable DR, and achieves high AUC on normal and referable DR tasks of 0.978 and 0.960, respectively, with 0.5 specificity. The method they suggest employs three networks: main, attention, and crop. The primary network employs the ImageNet-trained Inception model, with the attention network highlighting various types of lesions in the images and the crop network cropping the image with the highest level of attention.
4. DCNN (Deep Convolution Neural Network) was proposed by Yang et al. [3] for two stages of DR (normal and NPDR). The preprocessed data is fed into the two networks as input (local and global). Lesions are highlighted and graded over a global network. For the model's evaluation, they used class weight and kappa ratings. The PDR stage, on the other hand, was not taken into account in their research.
5. The Kaggle dataset proposed by Memon et al. [5] is used to test CNN architecture. The dataset was preprocessed, and they utilized nonlocal mean denoising with a delta value to get an equivalent level of brightness in the photos. The overall kappa score accuracy for evaluation is 0.74, and 10% of the photos were used for validation.
6. In [6], [7] ,the authors compared the Kaggle dataset's performance with various CNN algorithms. Garcia et al. [7]suggested a method that used CNN to both the right and left eye images individually (Alexnet, VGGnet16, etc.). To improve the contrast of the photos, the preprocessing and augmentation phases were applied to the dataset. They produced the greatest results on VGG16 with no fully linked layer, with a specificity of 93.65%, a sensitivity of 54.47, and an accuracy of 83.68 percent. DR phases, on the other hand, were not clearly categorised in their work.
7. The Kaggle dataset was used by Dutta et al. [6], who used three deep learning models (Feed Forward Neural Network (FNN), Deep Neural Network (DNN), and Convolutional Neural Network) (CNN). With a 7:3 validation split, they used 2000 photos out of 35128 images. They used a variety of preprocessing techniques (median, mean, standard deviation, and so on) before training their model on the training dataset. On DNN, the best training accuracy of 89.6% was achieved.

8. Usman and Khalid [8] presented using genetic programming (GP), also known as the intelligent feature set tuning (IFST) technology, a new method for detecting microaneurysms in fundus pictures. By constructing a mathematical phrase for classifying MA pictures with the MESSIDOR and DIARETDB1 datasets, they enhanced feature extraction and their numbers in the classification process.
9. The Haralick and anisotropic dual-tree complex wavelet transform (ADTCWT) technique was utilized for feature extraction from fundus pictures by Gayathri et al. [9] They presented binary and multiclass DR classification using the Haralick and anisotropic dual-tree complex wavelet transform (ADTCWT). To establish a valid DR classification, the scientists used the MESSIDOR, KAGGLE, and DIARETDB0 databases, as well as classifiers such as the support vector machine (SVM), random forest, random tree, and J48 approaches. Color retinal fundus images are used to classify them.
10. Jimenez et al. [15] proposed a technique for detecting microneurysms, which can be used for DR screening and early diagnosis. Exudates are whitish lesions with distinct borders. Long and colleagues
11. Long et al. [16] used dynamic threshold and fuzzy C-means clustering to explore the localisation of hard exudates, and the DIARETDB1 database images were categorised using support vector machines (SVM).
12. Baid et al. [17] designed a sophisticated system for the diagnosis of pathological myopia and optic disc segmentation for the detection of retinal abnormalities
13. Researchers have created classification systems for normal and DR eyes. Shirbahadurkar et al. [18] employed a teleophthalmology device and a hand-held fundus camera to capture retinal pictures. The method effectively distinguishes between normal and DR eyes.
14. Larsen et al. [19] described a system to classify eyes into normal and DR eyes by training the network on hemorrhages and microaneurysms.
15. Valverde et al. [20] proposed an algorithm for classifying microaneurysms, hemorrhages, and exudates in diverse lesions.

However, most of the associated study, particularly in the early stages of DR, is unable to appropriately define all of the stages of DR. It is critical to predict the DR early on in order to cure it, as later stages of the illness are difficult to cure and can cause to blindness. No other study, to our knowledge, has discovered the mild phases of DR, and by utilizing the private dataset that we used in our research. Our approach outperforms the present state of the art in detecting the mild stage.

3. Methodology

We employ the CRoss Industry Standard Process for Data Mining (CRISP-DM) methodology, a data-processing industry standard that ensures a systematic approach to meeting company goals. The data science life cycle is described by CRISP-DM in six phases, as seen here:1. Business understanding In our attempt to develop a system for mass screening to detect diabetic retinopathy, understanding business objectives aids in focusing on the right questions to Determine what the company need.2. Data Understanding Phase- This phase entails data cleaning and engineering Our main source comes from Al Rabea National Hospital in Mosul city, which contains this image data set images from multiple sources by technicians in this field and they are diagnosed by an expert ophthalmologist who rated them on a scale from 0 being no DR to 4 representing a proliferative stage.3. Data preparation- Convert data in preparation for the modeling where we reduced image collection has been adjusted to work on any laptop or desktop computer of reasonable size. step.4. Modeling- Create a model that addresses the business issue by These huge datasets have been verified to ensure that they reach an acceptable degree of quality and that the results are reliable. The key benefit of adopting a pre-trained model is that it saves time and money when it comes to training fresh deep learning models. 5. Evaluation-We evaluate models in a real-time application to record and forecast photos in real time, as well as assess how effectively the original business objectives are satisfied and Determine whether the model developed fits the above-mentioned business objectives.6. Deployment -Make your model accessible to users so they may engage with it but This phase is not included in this project and will be added in the future.

In our proposed system, we have hybridized the cnn algorithm consisting of five layers of convolutional layers with a 3 * 3 filter to train the network for early detection of the stages of development of diabetic retinopathy. Diabetes in all stages, as well as normal retinal images free of retinopathy, taken from the city of Mosul without information about the people, for the confidentiality of the case, and we classified them under the follow-up and supervision of an ophthalmologist. To benefit from it in the early detection of the disease and receiving treatment to prevent blindness.

4. Conclusion

The innovative DCNN algorithm was proposed as an algorithm that recognizes the retina and extracts features and properties by training the network on a set of samples. This algorithm has proven its efficiency in practice, and it has given the following conclusions:1-.The proposed algorithm does not need the input retinal images to be of fixed size. As the algorithm handles any size of image without a problem and its processing is fast.2-. Working with the proposed algorithm is very easy and it is suitable for users and programmers and it is possible to enter and use it in any application and any field because the algorithm requires images or samples of any subject for training only and then it is used and benefited from for different purposes automatically. Even training is done automatically.3- The proposed algorithm is very efficient, as it gave success rates ranging between (98.02%) and (99.6%) when applied to the database (Al-Rabea Al-Ahly Hospital) and the unrecognized images contained strong distortions.

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