Original Article

Diagnostic System Based on Deep Learning to Detect Diabetic Retinopathy

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ABSTRACT

Purpose: To develop a machine learning based diabetic retinopathy screening system to help ophthalmologists for initial level screening.

Study Design: Diagnostic accuracy study.

Place and Duration of Study: Haldwani in a private hospital from January 2023 to June, 2023.

Methods: A total of 229 fundus images (people suffering from diabetic retinopathy)were used which had micro aneurysms, soft exudates, hard exudates and hemorrhages. We classified these images and pre-processed them by scaling, orienting, and color adjustments. With the help of various pre-processing techniques, we decreased the size of our dataset so that it can be handled efficiently by our model with optimal resources. Visual Geometry Group (VGG) is a type of pre-trained deep convolutional neural network (CNN). The term "deep" refers to the number of layers; the VGG-16 uses 16 and VGG-19 uses 19 convolutional layers respectively. The model was tested on fresh retinal dataset.

Results: Our research has demonstrated promising results, achieving a high accuracy rate of 90% on a human dataset by utilizing VGG16 for feature extraction and a Logistic Regression classifier for classification.

Conclusion: Ophthalmologists can utilize this machine learning based screening system for diabetic retinopathy screening.

Key Words: Diabetic Retinopathy, Ophthalmology, Machine learning, Deep learning.

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INTRODUCTION

Diabetes is a chronic condition that, if left untreated, can lead to various complications, with permanent blindness being one of the most severe and devastating outcomes. Detecting and managing diabetes-related eye problems, such as diabetic retinopathy (DR), is crucial for preventing irreversible vision loss. One significant obstacle in addressing diabetic retinopathy effectively is the early identification of the disease progression to ensure timely and appropriate treatment. Traditionally, evaluating fundus images for signs of diabetic retinopathy has required skilled human assessment to accurately determine the disease stage. However, this manual process can be time-consuming and may not always result in consistent diagnoses.

The International Diabetes Federation (IDF) estimated that the global population with diabetes mellitus (DM) was 463 million in 2019 and is projected to reach 700 million by 2045.[1] According to a 2000 survey, diabetic retinopathy is very common in India (31.7 million cases), China (20.8), and the USA (17.7 million).[2] Ophthalmologists' standard photographic technique is a color fundus image. It takes a lot of effort and requires educated clinicians to manually evaluate color fundus pictures of the retina and detect DR. Due to a shortage of skilled physicians and an understanding of how to use sophisticated equipment in remote areas, this becomes difficult to screen every patient of diabetes. The expanding population of diabetics can be addressed by improving the infrastructure. Detailed planning and domain knowledge are required for traditional DR image classification systems. The key objective is to annotate the photos, which calls for the expertise of experienced ophthalmologists.

There are many frequently used machine learning (ML) techniques to forecast or classify a variety of health-related diseases.[3-5] Neural networks have been successfully used in the analysis and decision-making of drug discovery, medical image processing, and computer vision.[6,7] By assisting in pathological screening and disease prediction, the application of these cutting-edge machine-learning approaches has significantly reduced the burden of human interpretations.[8] Given their outstanding successes in various other healthcare fields, the employment of CNN and ML in the detection of diabetic retinopathy was a natural and inescapable focus of interest to decrease the incidence of diabetic retinopathy.

METHODS

It is necessary to gather fundus photographs from several datasets using a wide range of cameras, each image having a unique view, degree of clarity, degree of contrast, and image size, all of which are necessary for greater accuracy. Data augmentation includes various modifications including contrast and image flipping.[9-11]A total of 229 fundus images were used which belong to four categories Micro aneurysms, Soft Exudates, Hard Exudates and Hemorrhages. Our task was to classify these images.

Preparing images for use in model training and inference is known as image preprocessing.[12,13] This comprises but is not restricted to, scaling, orienting, and color adjustments.[14,15]With the help of various pre-processing techniques, we decreased the size of our dataset so that it can be handled efficiently by our model with optimal resources. To validate the accuracy of our developed model we have tested it with the help of an ophthalmologist on human data.

RESULTS

The best accuracy of our proposed work on human

Table 1: *Dataset Description.*

Severity Level	Training Images	Testing Images	Total Images
Micro aneurysms (MA)category	54 Images	27 Images	81 Images
Soft Exudates (SE)category	26 Images	14 Images	40 Images
Hard Exudates (EX)category	54 Images	27 Images	81 Images
Hemorrhages(HE)category	53 Images	27 Images	27 Images

Table 2: *VGG-16 Confusion matrix for following classifiers given below*

	Predicted (Confusion matrix plotted data for Logistic Regression)					
		Hemorrhages	**Hard Exudates**	**Micro-aneurysms**	**Soft Exudates**	**∑**
Actual	Hemorrhage	66	5	4	5	80
	Hard Exudates	1	72	7	1	81
	Microaneurysms	0	0	81	0	81
	Soft Exudates	4	0	0	36	40
	∑	71	77	92	42	282
	Predicted (Confusion matrix plotted data for Random Forest)					
		Hemorrhages	**Hard Exudates**	**Microaneurysms**	**Soft Exudates**	**∑**
Actual	Hemorrhage	64	8	3	5	80
	Hard Exudates	5	68	8	0	81
	Microaneurysms	5	1	75	0	81
	Soft Exudates	6	2	0	32	40
	∑	80	79	86	37	282
	Predicted (Confusion matrix plotted data for Neural Network)					
Actual	Hemorrhages	61	9	2	8	80
	Hard Exudates	0	74	6	1	81
	Microaneurysms	2	3	76	0	81
	Soft Exudates	4	1	0	35	40
	∑	67	87	84	44	282

Table 3: *VCG-19 Confusion matrix for the following classifiers given below*

		Hemorrhage	Hard Exudates	Micro-aneurysms	Soft Exudates	∑
	Predicted (Confusion matrix plotted data for Logistic Regression)					
Actual	Hemorrhage	69	3	4	4	80
	Hard Exudates	4	68	8	1	81
	Microaneurysms	0	2	79	0	81
	Soft Exudates	3	1	0	36	40
	∑	76	74	91	41	282
	Predicted (Confusion matrix plotted data for Random Forest)					
Actual	Hemorrhage	65	9	3	3	80
	Hard Exudates	11	62	7	1	81
	Microaneurysms	1	5	75	0	81
	Soft Exudates	9	1	0	30	40
	∑	86	77	85	355	282
	Predicted (Confusion matrix plotted data for Neural Network)					
Actual	Hemorrhage	64	8	3	5	80
	Hard Exudates	5	64	9	3	81
	Microaneurysms	0	5	76	0	81
	Soft Exudates	4	1	0	35	40
	∑	73	78	88	43	282

Table 4: *Inception v3 Confusion matrix for the following classifiers given below*

		Hemorrhage	Hard Exudates	Micro-aneurysm	Soft Exudates	∑
	Predicted (Confusion matrix plotted data for Logistic Regression)					
Actual	Hemorrhage	70	4	3	3	80
	Hard Exudates	1	71	8	1	81
	Microaneurysms	2	4	75	0	81
	Soft Exudates	4	2	0	34	40
	∑	77	81	86	38	282
	Predicted(Confusion matrix plotted data for Random Forest)					
Actual	Hemorrhage	62	4	4	10	80
	Hard Exudates	6	67	6	2	81
	Microaneurysms	1	4	75	1	81
	Soft Exudates	8	1	1	30	40
	∑	77	76	86	43	282
	Predicted (Confusion matrix plotted data for Neural Network)					
Actual	Hemorrhage	73	2	2	3	80
	Hard Exudates	1	69	9	2	81
	Microaneurysms	2	4	75	0	81
	Soft Exudates	4	0	0	36	40
	∑	80	75	86	41	282

dataset is 90% which is obtained when we have used VGG16 for feature extraction and Logistic Regression classifier for classification. According to the results, when an unseen new image is fed to our model it will categorize the image with an accuracy of 90%. With the help of an ophthalmologist, we have tested the model on 40 patient image records. Out of which 36 images were classified correctly and 4 images were classified incorrectly with the validation accuracy of 90%.

DISCUSSION

By leveraging advanced technologies like convolution neural networks (CNN) and other neural network models, we can enhance the speed and accuracy of diabetic retinopathy identification, potentially benefiting millions of individuals worldwide.

Early detection is a key in preventing diabetic retinopathy from progressing to a stage where vision loss becomes irreversible. Therefore, the development of a reliable and efficient screening process is essential to ensure timely intervention and improve patient outcomes. Introducing a system that can classify the different phases of diabetic retinopathy offers a promising solution to streamline the screening process and expedite treatment initiation.

TABLE 5: *A; Highest accuracy of 90.4 percent achieved for diabetic retinopathy screening using logistic regression. B; Highest accuracy of 89.4 percent achieved for diabetic retinopathy screening using Logistic Regression. C; Highest accuracy of 89.7 percent achieved for diabetic retinopathy screening using Neural Networks.*

A; VGG-16 Confusion matrix					
Model	**AUC**	**CA**	**F1**	**Precision**	**Recall**
SVM	0.975	0.872	0.871	0.876	0.872
Random Forest	0.967	0.848	0.847	0.847	0.848
Neural Network	0.971	0.872	0.871	0.875	0.872
Logistic Regression	***0.985***	***0.904***	***0.903***	***0.907***	***0.904***
Gradient Boosting	0.971	0.865	0.864	0.865	0.865
AdaBoost	0.807	0.723	0.719	0.723	0.723
B; VCG-19 Confusion matrix					
Model	**AUC**	**CA**	**F1**	**Precision**	**Recall**
SVM	0.974	0.837	0.834	0.843	0.837
Random Forest	0.962	0.823	0.822	0.824	0.823
Neural Network	0.975	0.848	0.847	0.848	0.848
Logistic Regression	***0.985***	***0.894***	***0.893***	***0.895***	***0.894***
Gradient Boosting	0.976	0.876	0.875	0.878	0.876
AdaBoost	0.874	0.816	0.815	0.814	0.816
C; Inception v3Confusion matrix					
Model	**AUC**	**CA**	**F1**	**Precision**	**Recall**
SVM	0.976	0.894	0.893	0.895	0.894
Random Forest	0.953	0.830	0.830	0.831	0.830
Neural Network	***0.981***	***0.897***	***0.897***	***0.898***	***0.897***
Logistic Regression	0.980	0.887	0.886	0.887	0.887
Gradient Boosting	0.975	0.894	0.894	0.894	0.894
AdaBoost	0.810	0.727	0.726	0.730	0.727

Visual Geometry Group (VGG) is a type of pre-trained deep convolutional neural network (CNN).[16,17] The term “deep” refers to the number of layers; the VGG-16 uses 16 and VGG-19 uses 19 convolutional layers respectively. Using the VGG architecture, creative item identification models were created.Inception-v3 also lies in the category of convolutional neural network which is 48 layers deeper.[18] A type of pre-trained model architecture that has been trained on more than a million photographs of the ImageNet database. Since the original ImageNet dataset did not contain a “background” class and the Tensor Flow version of Inception V3 was trained on 1,000 classes from the original ImageNet dataset, which was trained using more than 1 million training images. Various machine learning techniques are used to detect diabetic retinopathy previously. But we have used transfer learning machine learning approaches with attention mechanism. To extract features for this paper, we employed three pre-trained models: VGG16, VGG19, and inception V3.20 then, we applied traditional and deep learning machine learning methods like SVM, Random Forest, Neural Networks, Gradient boosting, and Logistic Regression for DR image categorization. In the future, we shall upgrade our model with more recent deep-learning techniques to generalize our model.

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Patient’s Consent: Researchers followed the guidelines set forth in the Declaration of Helsinki.

Conflict of Interest: Authors declared no conflict of interest.

Ethical Approval: The study was approved by The Institutional Review Board/Ethical Review Board **(GEHU/BMT/001465).**

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Authors Designation and Contribution

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Janmejay Pant; Assistant Professor: *Literature search, Data acquisition, Data analysis, Statistical analysis.*

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