Automatic Severity Classification Of Diabetic Retinopathy Based On Convolutional Block Attention Module

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Abstract- *Diabetic Retinopathy is a complication developed due to heightened blood glucose levels is deemed one of the most sight-threatening diseases. Unfortunately, DR is screening manually acquired by an ophthalmologist, a process that can be considered as erroneous and time consuming. Accordingly, automated DR diagnostics have become a focus of research in recent years due to the tremendous increase in diabetic patient. The recent accomplishments demonstrated by Convolutional Neural Networks settle them as state-of-the-art for DR stage identification. The paper proposes a new automatic deep learning based approach for severity detection by utilizing a single Color Fundus photograph . The proposed technique employs DenseNet169's encoder to construct a visual embedding. Furthermore, Convolutional Block Attention Module is introduced on top of the encoder to reinforce its discriminative power. Finally, the model is trained using cross-entropy loss on the Kaggle Asia Pacific Tele-Ophthalmology Society's dataset. On the binary classification task, we accomplished as 97% accuracy - 97% sensitivity - 98.3% specificity - 0.9455, Quadratic Weighted Kappa score compared to the state-of-the-art. Our network showed high competency for severity grading. The significant contribution of the proposed framework is that it efficiently grades the severity level of diabetic retinopathy while reducing the time and space complexity required, which demonstrates it as a promising candidate for autonomous diagnosis.*

Keywords- Screening, Contribution, Deep learning

I. INTRODUCTION

Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be image or characteristics features associated with that image. The image processing is among rapidly growing technologies. It forms core research area within engineering and computer science disciplines too. Image processing basically includes the following three steps: • Importing the image via image acquisition tools. • Analyzing and manipulating the image. • Output in which result can be altered image or report that is based on image analysis. There are two types of methods used for image processing namely, analogue and digital image processing. Analogue image processing can be used for the hard copies like printouts and photographs. Image analysts use various fundamentals of interpretation while using these visual techniques. Digital Image Processing techniques help in manipulation of the digital images by using computers. The three general phases that all types of data have to undergo while using digital technique are pre-processing, enhancement, and display, information extraction.

Medical image analysis is the process of extracting meaningful information from medical images, often using computational methods. Some of the tasks for medical image analysis are visualization and exploration of 2D images and 3D volumes, segmentation, classification, registration, and 3D reconstruction of image data. The images for this analysis can be obtained from medical imaging modalities such as x-ray, ultrasound, Computed Tomography, Magnetic Resonance Imaging, Nuclear Imaging, and microscopy. It has a development environment and built in analysis and data access functionality for building algorithms for medical image analysis.

Diabetic Retinopathy is an eyes disorder in the patients suffering from diabetes. Damage to the blood veins of the retina causes this disease. Diabetic retinopathy symptoms such as Microaneurysm, Exudate Hemorrhage, Cotton Wool Spot can be seen on color fundus retinal imaging, according to several scientific investigations. Microaneurysm is a swelling in the retinal blood veins that looks as a sharp-edged red spot on the retinal surface. Protein loss from tiny retinal veins causes exudates, which are white or pale yellow patches in the retina. Hemorrhages are deposits that look like red spots with non-uniform borders and are caused by thin and weak blood veins leaking. Non-Proliferative Diabetic Retinopathy and Proliferative Diabetic Retinopathy are the two types of

Diabetic Retinopathy. Based on the progression of lesions, the NPDR is then classified as `mild', `moderate', or `severe'. Mild DR is the earliest stage at which Micro Aneurysms form. Blood vessel swelling occurs when the illness advances to a moderate level, resulting in impaired vision. During the severe stage, abnormal blood veins development is observed. The last stage of DR is the PDR, in which extensive retinal fractures and detachment occur, resulting in complete blindness. The DR is dangerous because in some cases, when not identified in early levels it will get the patient permanently blind. The patients suffering from DR have 25% more chances of permanent blindness than the people without DR. As a result, globally in persons aged 20 to 65, the leading cause of blindness is DR.

DR-related blindness can be avoided by frequent retinal checkups. The ophthalmologists use manual techniques to detect the DR. It manually look at the color of retinal images of the patient and then identify the level of the DR. The method is very complex and buggy, and it also consumes a lot of time to detect the DR. The timely detection of the DR can save many people from the permanent blindness. Many Machine Learning and Deep Learning based DR detection techniques have been proposed in recent years. The investigate the efficency of light-weight deep learning architecture for fast and robust severity grading of diabetic retinopathy. Our framework is based on a modified version of DenseNet with integrating an attention mechanism with the former architecture for more feature refinement. The observe of the effect of data imbalance on the model performance and mitigate such an effect by using an imbalanced learning technique. The first pass and preprocess the retinal image for quality enhancement, afterward, the images were passed to the DenseNet encoder C for feature extraction, then the features are sent to the attention module A for more improved representation. It train our model by freezing Densnet’s encoder, trained on the ImageNet dataset for the model’s convergence acceleration by using the pretrained weights and training only the attention module and the classification head using APTOS data.

The developed a modified architecture to reduce the time needed for training and inference while enhancing DR severity grading by using a relatively small model with 8.5 million parameters compared to 10.8 million in the previous work.

The exploited the effect of using an attention mechanism as a supplementary module for feature refinement which led to an increase in accuracy while preserving low model complexity.

The tested the effect of using an imbalanced learning approach to alleviate the impact of data imbalance on the model’s performance and proved its efficiency in enhancing the overall metrics.

Utilized transfer learning only by freezing the convolutional encoder without extra fine-tuning which led to relatively low number of learnable parameters.

II. LITERATURE SURVEY

Diabetic Retinopathy (DR) is an eye abnormality in which the human retina is affected due to an increasing amount of insulin in blood. The early detection and diagnosis of DR is vital to save the vision of diabetes patients. The early signs of DR which appear on the surface of the retina are microaneurysms, haemorrhages, and exudates. In this work, we propose a system consisting of a novel hybrid classifier for the detection of retinal lesions. The proposed system consists of preprocessing, extraction of candidate lesions, feature set formulation, and classification. In preprocessing, the system eliminates background pixels and extracts the blood vessels and optic disc from the digital retinal image. The candidate lesion detection phase extracts, using filter banks, all regions which may possibly have any type of lesion. A feature set based on different descriptors, such as shape, intensity, and statistics, is formulated for each possible candidate region: this further helps in classifying that region. This paper presents an extension of the m-Mediods based modeling approach, and combines it with a Gaussian Mixture Model in an ensemble to form a hybrid classifier to improve the accuracy of the classification.

Computer-aided screening system (DREAM) that analyzes fundus images with varying illumination and fields of view, and generates a severity grade for diabetic retinopathy (DR) using machine learning. Classifiers such as the Gaussian Mixture model (GMM), k-nearest neighbor (kNN), support vector machine (SVM), and AdaBoost are analyzed for classifying retinopathy lesions from nonlesions. GMM and kNN classifiers are found to be the best classifiers for bright and red lesion classification, respectively. A main contribution of this paper is the reduction in the number of features used for lesion classification by feature ranking using Adaboost where 30 top features are selected out of 78. A novel two-step hierarchical classification approach is proposed where the nonlesions or false positives are rejected in the first step. In the second step, the bright lesions are classified as hard exudates and cotton wool spots, and the red lesions are classified as hemorrhages and micro-aneurysms. This lesion classification problem deals with unbalanced datasets and SVM or combination classifiers derived from SVM using the

Dempster-Shafer theory are found to incur more classification error than the GMM and kNN classifiers due to the data imbalance.

Human eye is one of the most sophisticated organ, with retina, pupil, iris cornea, lens and optic nerve. Automatic retinal image analysis is emerging as an important screening tool for early detection of eye diseases. Uncontrolled diabetes retinopathy (DR) and glaucoma may lead to blindness. DR is caused by damage to the small blood vessels of the retina in the posterior part of the eye of the diabetic patient. The main stages of DR are non-proliferate diabetes retinopathy (NPDR) and proliferate diabetes retinopathy (PDR). The retinal fundus photographs are widely used in the diagnosis and treatment of various eye diseases in clinics. It is also one of the main resources used for mass screening of DR. We present an automatic screening system for the detection of normal and DR stages (NPDR and PDR). The proposed systems involves processing of fundus images for extraction of abnormal signs, such as area of hard exudates, area of blood vessels, bifurcation points, texture and entropies. Our protocol uses total of 156 subjects consisting of two stages of DR and normal.

Diabetic retinopathy (DR) is a leading cause of blindness, but determining the presence of various small features requires an experienced ophthalmologist, which is time-consuming and difficult. Convolution neural network (CNN), which can learn hierarchical and discriminative features without clinician experience, is an alternative method to address the aforementioned issue. In this paper, we look at four aspects of using deep CNN to solve the DR classification problem: network architectures, preprocessing, class imbalance, and fine-tuning. Our best performance was 79% accuracy, compared to 75% accuracy for Harry's scheme.

An accurate detection and classification of diabetic retinopathy is critical to better assess the disease and possibly slow down its progression. Several methods are used for the diagnosis of diabetic retinopathy including dilated eye examination, fluorescein angiography, optical coherence and fundus photography. In this work, a 2D convolutional neural network is introduced for the analysis and classification of fundus images into one of the four main stages of diabetic retinopathy. A training accuracy of 99.9% and a Leave One out Cross Validation testing accuracy of 80.2% were achieved after training 101 fundus images representing 4 different stages of the disease for 50 epochs. ting cancer cell lines of different metastatic ability.

Diabetic retinopathy (DR) is one kind of eye disease that is caused by overtime diabetes. Lots of patients around the world suffered from DR which may bring about blindness. Early detection of DR is a rigid quest which can remind the DR patients to seek corresponding treatments in time. This work presents an automatic image-level DR detection system using multiple well-trained deep learning models. Besides, several deep learning models are integrated using the Adaboost algorithm in order to reduce the bias of each single model. To explain the results of DR detection, this paper provides weighted class activation maps (CAMs) that can illustrate the suspected position of lesions. In the pre-processing stage, eight image transformation ways are also introduced to help augment the diversity of fundus images. Experiments demonstrate that the method proposed by this work has stronger robustness and acquires more excellent performance than that of individual deep learning model.

Diabetic retinopathy (DR) is a major cause of human vision loss worldwide. Slowing down the progress of the disease requires early screening. However, the clinical diagnosis of DR presents a considerable challenge in low-resource settings where few ophthalmologists are available to care for all patients with diabetes. In this study, an automated DR identification and grading system called DeepDR is proposed. DeepDR directly detects the presence and severity of DR from fundus images via transfer learning and ensemble learning. It comprises a set of state-ofthe-art neural networks based on combinations of popular convolutional neural networks and customised standard deep neural networks. The DeepDR system is developed by constructing a high-quality dataset of DR medical images and then labelled by clinical ophthalmologists. In further explore the relationship between the number of ideal component classifiers and the number of class labels, as well as the effects of different combinations of component classifiers on the best integration performance to construct an optimal model.

III. PROPOSED SYSTEM

Our algorithm consists of a backbone model (convolutional base) and an attention module. First, the backbone network is used as a feature extractor for the input fundus image, andn features are refined using Convolutional Block Attention Module (CBAM) for data representation enhancement.

Afterward, converting them to a one-dimensional array by averaging each feature map generated by the attention module using Global Average Pooling (GAP) followed by classification head.

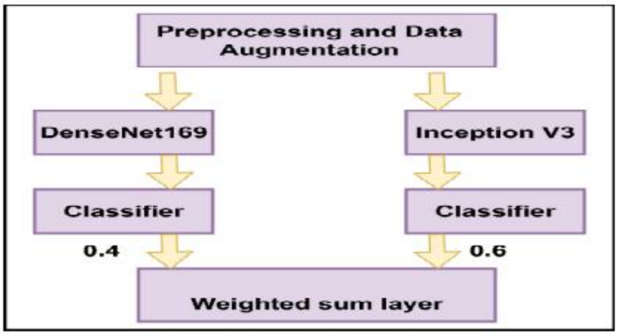


Fig 1 Block Diagram of Proposed System

Machine learning model is built with different algorithms that are trained by information and data set provided which predict new classification as fraud or not These algorithms implemented for building model that is trained using historical data and that predict unseen data with most matching features. And then model is tested and validated to evaluate its performance. After the calculations comparison is made. For automobile insurance fraud detection shows the higher accuracy.

IV. MODULES DESCRIPTION

Data Pre-Processing

Image preprocessing is the steps taken to format images before they are used by model training and inference. • Here preprocessing phase have three parts, such as image resizing, Dirty Image Removal and Data Augmentation.

Image Resizing • Image resizing is necessary when you need to increase or decrease the total number of pixels • Our models train faster on smaller images. • An input image that is twice as large requires our network to learn from four times as many pixels.

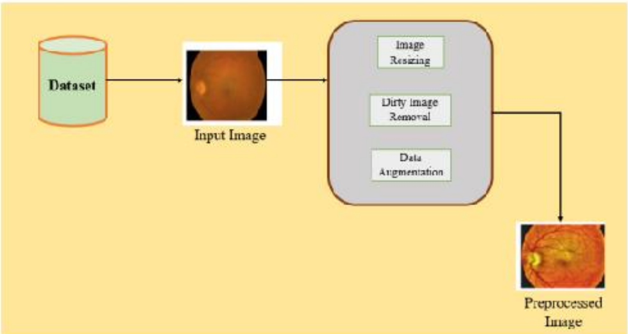


Fig 2 Structure of Image Processing

Dirty Image Removal • Removing part of an image refers to the process of destroying image data in certain regions of an image. Data Augmentation • Data augmentation is a technique of artificially increasing the training set by creating modified copies of a dataset using existing data. • It includes making minor changes to the dataset or using deep learning to generate new data points.

Feature Extraction

Investigating APTOS data revealed severe class imbalance, i.e., 49.29%, 10.1%, 27.28%, 5.27%, 8.05%belonging to normal, mild, moderate, severe, and proliferative DR grades.Furthermore, by its projection in lower-dimensional feature space, using Principle Component Analysis (PCA) to lower the data dimensionality to 500-D followed by applying the t-Distributed Stochastic Neighbor Embedding (t-SNE) algorithm to analyze data distribution across different class.

Class 0 forms feature clusters all over the 2-D space, making it one of the easiest classes to be detected.

Classes (1-4) have acute overlapping, which generates a challenging task for the algorithm to fit a proper hyperplane.
They artificially clustered the data to form only two regions (infected and healthy), and observed that DL, based on our understanding, is robust enough to solve the binary classification problem.

DenseNet

DenseNet was used as the main backbone for the proposed approach. ϖ The demonstrated the robustness of the architecture against the vanishing gradient problem while reducing the number of parameters and reducing over-fitting for smaller datasets. ϖ The main idea was to connect CNN layers using a dense connectivity pattern such that each layer has a concatenated input of all preceding feature maps.

Ensemble learning is a way of generating various base classifiers from which a new classifier is derived which performs better than any constituent classifier. • DR has five stages or classes, namely normal, mild, moderate, severe and PDR (Proliferative Diabetic Retinopathy).

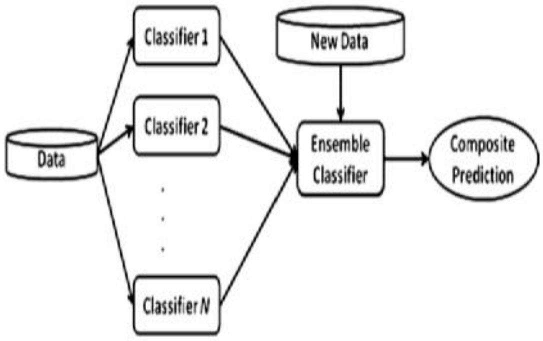
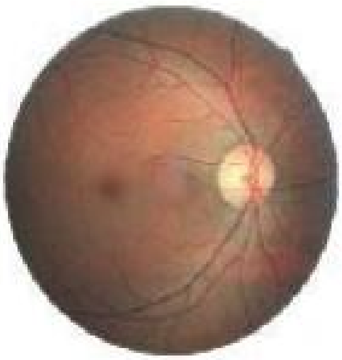


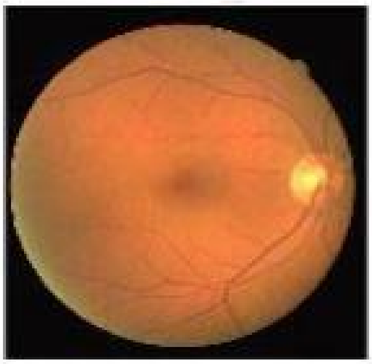
Fig 3 Structure of Ensemble Classification

The suggested approach uses CNN-based networks for feature extraction. Our approach use two streams of inputs in the form of features extracted from the two deep networks. The features extracted from these networks then fused and fed to the classification model.

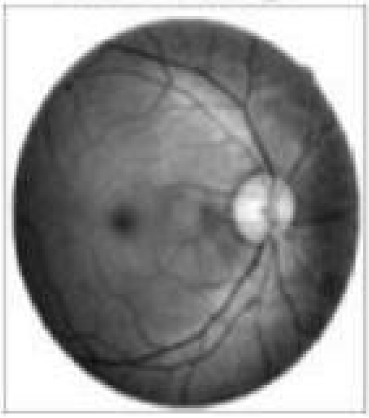
V. SCREEN SHOTS



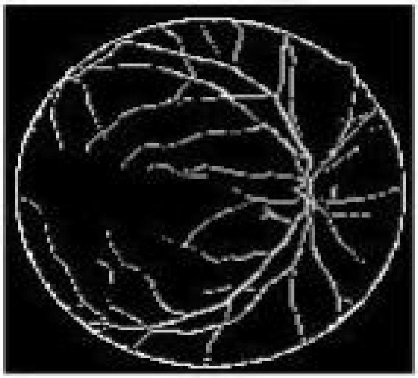
Input Image



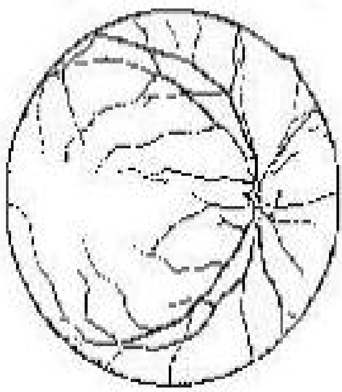
Testing Image 1



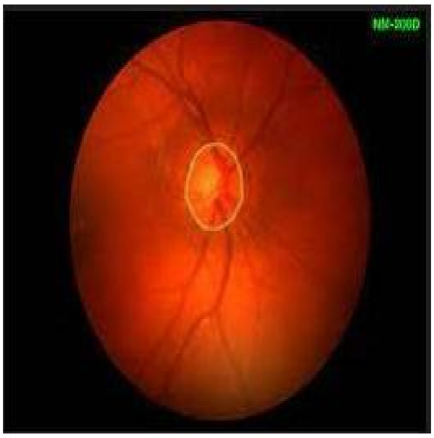
Filtering Image 1



Clean Image 1



Filtered Layer 1



Final detection image

VI. CONCLUSION

In this work, they exploited a new CNN model based on DenseNet169 architecture integrated with CBAM as an additional component to be added for representational power enhancement. The proposed method demonstrated robust performance and comparable quality metrics while reducing the burden of space and time complexity. Furthermore, a 2-D Gaussian filter enhances fundus images' quality. Finally, we used INS to form our weighted loss function to tackle the class imbalance to improve the model's prediction across all classes. For future research direction, we evaluate the performance of different CBAM configurations. Moreover, experimenting with different imbalanced learning techniques and increasing the dataset size will lead to better performance Future work, to extend our deep learning algorithm in future to work in an uncontrolled environment and will replace our current dimensionality reduction PCA technique with auto encoders to increase the accuracy of our proposed approach. More testing on real-world circumstances is necessary for clinical applications, and the system should be made more robust to run-on low-cost devices for quick response. As compared to manual diagnosis, the automated approaches are quicker and enables the doctors to consult more patients in lesser time. In near future, compact deep learning solutions for multiple devices with better accuracy will be in great demand.

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