IMPROVING THE PERFORMANCE OF THE GRADIENT MULTILEVEL DAM (GM-DAM) TO INCREASE THE ACCURACY IN DETECTING AND CLASSIFICATION OF DME IMAGES

[1]Syed Thisin, [2]G Mahesh, [3]A.Geetha, [4]J Revanth
[1,2,3]Assistant Professor, [4]UG Student, [1,2,3,4]Department of Computer Science Engineering, Visvesvaraya College of Engineering & Technology, Hyderabad, India.

Abstract
Diabetes-related macular edoema (DME) is a retinal condition that can cause vision loss if early preventative measures are not implemented. Early diagnosis of diabetic retinopathy may lead to DME, which further aids in preventing blindness. Currently, professionals are using a manual technique to try to find the DME in the OCT picture. Detecting the DME is a more difficult and time-consuming task. The suggested approach is focused on identifying DME-affected photos and images that are not impacted by DME. This study introduces Multi-dimensional Amalgamate Classification Using Optical Coherence Tomography (OCT) to address the challenges in DME detection. The Gradient Multilevel DAM (GM-DAM) is used to recognize and classify DME pictures more accurately, which enhances performance. Experimental results show the performance of proposed system.
Keywords: OCT, AMD, DMA, GM-DAM

Introduction

Today, OCT is a very effective imaging technique that can assess a variety of retinal abnormalities [1–3], including the diagnosis of Choroidal Neovascularization (CNV) and Diabetic Macular Edema (DME). The problem of diagnosing illnesses in the human body is quite challenging; in particular, one should concentrate on the primary applications of artificial intelligence (AI). Businesses like Google [4] and GE Healthcare [5] are increasing their investments in the health industry. Numerous healthcare systems concentrate on illness diagnosis using various methods. Due to the unpredictable nature of eye illnesses, detection and diagnosis are extremely sensitive.

The person's diabetic range determines the status, or severity and circumstance, of the DME. The possibility of DMA infection exists if the individual has diabetes. Many medical experts presently diagnosing based on fundus and retinal images. If the overall patients are increasing day-by-day, the total no of diagnosing process is also increased. The proposed system is focusingon providing the automated detection that shows the infected region with highlighted color. Fromthe past research, it is observed that integrating deep learning algorithms achieves the more accuracy.

In this study, we created a model to identify COVID-19 pneumonia using chest X-ray pictures. We used a dataset of 392 X-ray patient pictures with positive and negative COVID results that was made accessible to the public for this project. Each input image's size was set to 224 224 3 and CNN training was run to ensure accuracy. With a kernel size of 3 3, we built three convolutional layer-based models. We still have a pressing need to determine the infection's level of severity. Future research will involve testing COVID-19 detection on chest CT scan image data and combining both models to determine the severity level. We also use sophisticated techniques for early COVID19 infection identification based on voice recognition.

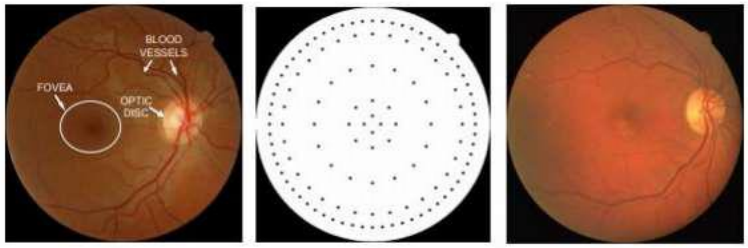

Figure 1 (a) Figure 1 (b) Figure 1 (c)

Figure 1 (a) (b) (c) Normal Eye Images

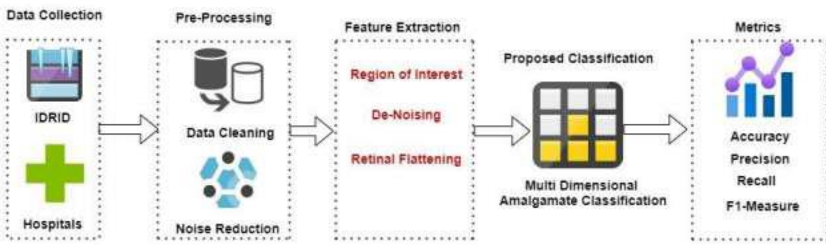

Figure 2: System Architecture

Literature Survey

In this section various deep learning algorithms are discussed that are applied on OCT images and also discussed about the performance of existing algorithms.

The author [6] proposed the new deep CNN model that detects the AMD, the accuracy of this method is 91.20%, sensitivity is 93.10% and specificity is about 89.10% by utilizing the blindfold cross-validation technique, with the accuracy of 96.12%, sensitivity is 97.12% and specificity is of 94.12% by utilizing ten-fold cross-validation technique.

The author in [7] integrated the DL algorithms dynamically to detect the diabetic retinopathy and DME and these are applied on fundus images, the performance is calculated by showing AUC is 0.991, sensitivity is 91.1%, specificity is 98.2% and the AUC is 88%, sensitivity and 98.5% specificity which is obtained by using EyePACS-1 and Messidor-2 dataset. These methods perform better when compare with other techniques, for training the CNN raw images are used from the starting which is require huge amount of data for training and computation time to get the better accuracy.

The new intelligent deep learning based algorithm is developed to detect and divide the multi- typed abnormalities and it is automatically applied on OCT images, the accuracy (96.1%), sensitivity(95%), specificity (97.1%) and also with mean AUC is 0.987 is observed. The author

[8] is focused on dividing the image dataset randomly with the following steps such as training, validating and testing at the image level. This can be applicable for the multiple images that are included with the different partition. The performance of this model is biased.

The author [9] developed the new method called as DL method which is based on visual geometry group 16 (VGG-16) networks and this classifies the AMD and DME within the OCT images, the accuracy (98.8%), sensitivity and specificity (99.7%) and AUC is 100%.

The author [10] developed the new learning method that is based on initiation network to find the retinal abnormalities present in the retinal OCT images efficiently. The performance for this model is calculated by using accuracy for all the classes such as normal, AMD, and DME were 98.99%, 88.99%, and 87%. To increase the training process gradient vanishing is to be integrated. The analysis parameter (only accuracy) was not considerable. The author mainly focused on diagnosing two diseases and normal. The classifiers with multiclass features specify the abnormality between the given samples.

The author [11] proposed a Lesion-Aware CNN (LA-CNN) technique to divide the OCT images by using retinal lesions that are detected by using lesion detection network (LDN) within the given dataset and this technique follows the CNN to get the more significant data from the infected region to achieve the efficient classification with accuracy of 91.1% and sensitivity is 99.44% which are obtained by using UCSD dataset.

The author [12] developed the ensemble approach that uses the multi-scale convolutional mixture of expert (MCME) that classifies the normal retina, dry AMD and DME, getting the performance with precision rate of 99.10% and AUC is 0.9967% with the proposed model that utilizes the 4 scale-dependent experts. In this approach, the structure is more complex within DL network which very high. This model is applied on OCT images dataset which gets more accurate predictions. S.Venkataramana et al., [13] proposed a revised Low Energy Adaptive Clustering Hierarchy (LEACH) protocol which balances the Security-Energy trade-offs. S.Venkataramana et al., [14] proposed classification of handwritten digits based on Convolution Neural Networks (CNN). B V D S Sekhar et al., [15] proposed a new algorithm with detection of Coronary Artery Disease (CAD). M.Mounika et al., [16] proposed a new algorithm that controls the robot with the colored object. Hence, robots with Vision Guided Systems are much more efficient.

Dataset Description

Methods to Evaluate Segmentation and Indexing Techniques (MESSIDOR) is the dataset consists of 272 fundus color images which are having 102 testing images and 170 training images. The pixels of the images are gathered from 8 bits per color plane at 1440*960, 2240*1488 or 2304*1536.

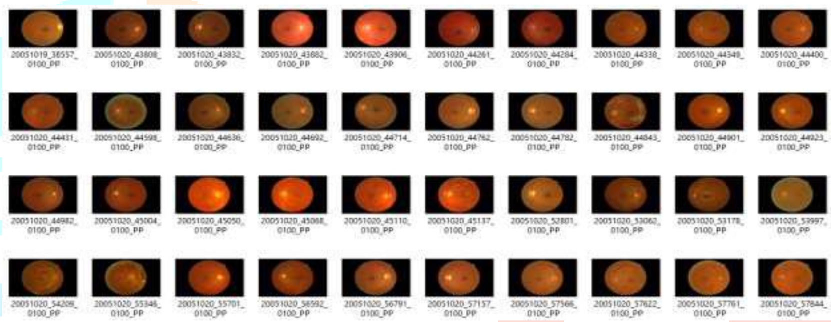

Figure 3: Dataset images Samples

For the every image two diagnoses are provided such as

- Grade of Retinopathy.
- Macular Edema risk.

Multi-dimensional Amalgamate Classification (MDAC)

The segmentation of medical images is more complex when compare with normal images. Especially, OCT images require more accurate segmentation process to get the accurate result i,e to get better disease prediction. The MDAC is the combination of Gradient Multilevel DAM (GM-DAM) and advanced segmentation is integrated. This model is used to classify two common macular diseases, age-related macular degeneration (AMD) and diabetic macular edema (DME) from normal macular eye conditions using optical coherence tomography (OCT) images. The proposed system is also called as Multi-layered deep neural network and this is the combination of multiple layers that analysis the every input image and observe the diseases and then classify. The following are the steps that carried out the process of detecting DME.

Step 1: Initialize dataset with collected fundus images which are examined by retinal specialisti,e dataset is ready for training and testing.

Step 2: The initial frame work is pre-trained and pre-trained weights are fine-tuned using the pre-processing steps like data cleaning, noise reduction.

Step 3: Feature Extraction.

Step 4: Apply Multi-dimensional Amalgamate Classification algorithm consists of GM-DAMfor the above trained data set.

Step 5: By using parameters calculate the results of our proposed system.

Experimental Results

The implementation is developed by using Python programming language with Win-Python as IDE (Integrated development Environment). In python, keras-pandas are more useful to develop and iterate on deep learning models. Only keras cannot get the formatted data but merging keras and pandas faces some challenges and overcomes to improve more accuracy.

Performance Analysis

The performance is evaluated by using various parameters such as TP (true positive), TN (true negative), FP (false positive) and FN (false negative). The evaluation metrics include accuracy, F1-score, precision, recall.

Accuracy: This is very important parameter that initializes the total number of exactly classified data

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{FP} + \text{TP} + \text{FN}}$$

instances over the total number of data instances.

Precision: When the FP is high the precision helps. If the precision is low, then the patients willbe told that they are affected with AMD infection; this may show some mistakes within the tests.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall: Recall is calculated when the false negatives are high.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

F1 score - This consider the weighted average of Precision and Recall. If the score consider the false positives and false negatives into account. It is not an easy to understand the accuracy. F1 ismore utilized than accuracy.

$$\text{F1 Score} = 2 * \frac{(\text{Recall} * \text{Precision})}{(\text{Recall} + \text{Precision})}$$

	Accuracy	**Precision**	**Recall**
WCME	93.40	94.35	93.41
Multilevel DAM	96.50	98.11	96.62
Gradient	97.00	98.21	96.92
Multilevel DAM			

Table 1: Performance comparison between Existing and Proposed Models showingaccuracy, precision and recall

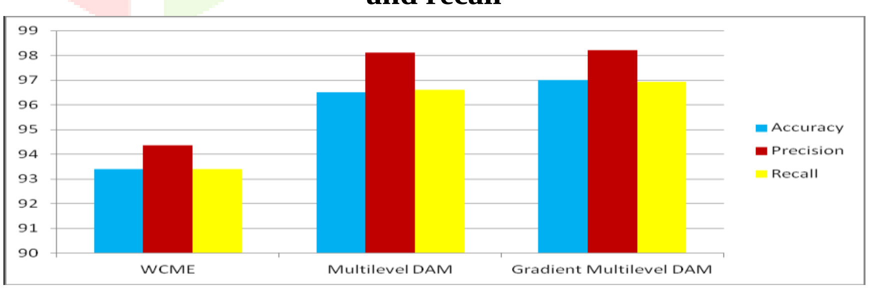

Figure 4: Comparison graph between WCME, M-DAM, GM-DAM

	F1-Score	**AUC**	**Duration (Milli Sec)**
WCME	0.933	0.973	0.97
Multilevel DAM	0.954	0.984	0.98
Gradient MultilevelDAM	1.41	1.78	0.86

Table 2: Performance comparison between Existing and Proposed Models showing F1-Score, AUC, Duration (milli seconds)

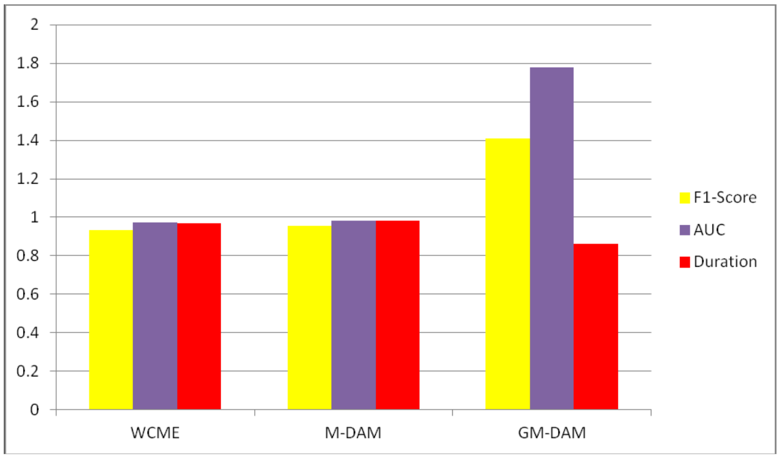

Figure 5: Comparison graph between WCME, M-DAM, GM-DAM

Conclusion

In order to classify the DME illness, the MDAC is introduced in this research along with the integration of sophisticated OCT picture segmentation. The gradient DME is most frequently and intensely utilized to identify the illness. Any sort of imaging, including X-ray and CT scan images, can be used for this. Finding the infectious areas within the available samples depends heavily on segmentation. The MDAC has greater potential for resolving tiresome OCT picture segmentation problems. This method may be applied to a variety of situations to identify different retinal disorders.

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