AUTONOMOUS RETINAL IMAGE ANALYSIS AND CONTENT-BASED RETRIEVAL SYSTEM FOR DIAGNOSING DIABETIC RETINOPATHY USING DEEP CONVOLUTIONAL FEATURE EXTRACTION

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DECLARATION

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ABSTRACT

The automatic classification and content-based image retrieval (CBIR) for a given retinal image of diabetic retinopathy (DR) are very essential since this is the leading source of permanent loss of vision in the working-age individuals all over the world today. Current clinical approaches require a well-trained clinician to manually evaluate fundus photographs of retina and locate lesions associated with vascular abnormalities due to diabetes, which is time-consuming. The principal objective of this research is to classify the severity level and retrieve semantically similar retinal imageries to a given query image for effective treatment.

Recently, deep CNN-based feature extraction has been used to predict DR from fundus images with reasonable accuracy whereas effective and comprehensive deep retinal image retrieval model for DR is not available in the literature. However, techniques such as singular value decomposition (SVD), global average pooling (GAP) and ensemble learning have not been used in automatic prediction of DR.

In this research, it is suggested a combination of deep features extracted from an ensemble of pretrained-CNNs (VGG-16, ResNet-18, and DenseNet-201) as a single feature vector to accomplish the research objectives. The experimental outcomes of this research demonstrate a promising accuracy of over 98% for both tasks. A classification model was built as the first step and then it was extended it to a retrieval model by using a deep supervised hashing approach in order to perform efficient retinal image retrieval, where it implicitly learn a good image representation along with a similarity-preserving compact binary hash code for each image. This research was evaluated using prominent CNN architectures (VGG, ResNet, InceptionResNetV2, InceptionV3, Xception, and DenseNet) that can be used for transfer learning. Moreover, GAP and SVD were used as dimensional reduction techniques in order to diminish processing time and memory utilization while preserving classification accuracy and retrieval performance.

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LIST OF ABBREVIATIONS

AAO American Academy of Ophthalmology

AUC Area Under Curve

CNN Convolutional Neural Network

ANN Artificial Neural Network

DR Diabetic Retinopathy

CBIR Content-based Image Retrieval

GAP Global Average Pooling

SVD Singular Value Decomposition

SGD Stochastic Gradient Descent

mAP mean Average Precision

SVM Support Vector Machine

RBF Radial Basis Function

NPDR Non-Proliferative Diabetic Retinopathy

PDR Proliferative Diabetic Retinopathy

KSH Supervised Hashing with Kernels

MLH Minimal Loss Hashing

SH Spectral Hashing

LSH Locality Sensitive Hashing

ReLU Rectified Linear Unit

LBP Local Binary Patterns

DT-CWT Dual-Tree Complex Wavelet Transform

LGN Lateral Geniculate Nucleus

OCT Optical Coherent Tomography

WHO World Health Organization

MA Microaneurysm