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Self-Organized Operational Neural Networks for Early GlaucomaDiagnosis in Digital Fundus Images

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1. ABSTRACT

Glaucoma leads to permanent vision disability by damaging the optical nerve that transmits visual images to the brain. The fact that glaucoma does not show any symptoms as it progresses and cannot be stopped at the later stages, makes it critical to be diagnosed in its early stages. Although various deep learning models have been applied for detecting glaucoma from digital fundus images, due to the scarcity of labeled data, their generalization performance was limited along with high computational complexity and special hardware requirements. In this study, compact Self-Organized Operational Neural Networks (Self-ONNs) are proposed for early detection of glaucoma in fundus images and their performance is compared against the conventional (deep) Convolutional Neural Networks (CNNs) over three benchmark datasets: ACRIMA, RIM-ONE, and ESOGU. The experimental results demonstrate that Self-ONNs not only achieve superior detection performance but can also significantly reduce the computational complexity making it a potentially suitable network model for biomedical datasets especially when the data is scarce.

2. INTRODUCTION

Glaucoma, also called the silent thief of sight,"" leads to permanent vision disability by damaging the optic nerve. According to the World Health Organization (WHO) data, glaucoma is the leading cause of irreversible blindness globally.

Because the optic nerve head damage caused by glaucoma is irreversible, early diagnosis and treatment is crucial. However, mild glaucoma does not show any symptoms such as pain or blurred vision, hence its detection can be challenging especially for large-scale screening purposes. Although the previous worldwide estimate of the number of adults with glaucoma was 64.3 million in 2013, projections show that this figure will rise by 74% to 111.8 million in 2040.

The optic nerve head damage in glaucoma can be diagnosed using various clinical tools including but notlimited to fundoscopy, visual field examination, optical coherence tomography and digital fundus imaging. Recently thanks to its non-invasive, cost-effective, and rapid nature, digital fundus images have been proposed as an effective means of exploiting signal processing and machine learning techniques for the automated assessment of the optic nerve head in a large-scaleglaucoma screening setting,
Several methods for the automatic detection of glaucoma have been proposed in the literature. transformed color fundus images to eigen images by principal component analysis and classified using a support vector machine (SVM) to obtain a Glaucoma Risk Index (GRI) with competitive Glaucoma detectionperformance.

a glaucoma detection system using wavelet transform features to extract energy signatures and applied different feature ranking and feature selection strategies.They classified these features by SVM and obtained 93% accuracy using a local dataset. Carillo et al. proposed a computational tool based on the optic disc (OD) and cup segmentation algorithm a method for glaucoma diagnosis. At first EWT was used to image breakdown into various frequency bands.After that correntropy features were obtained. Then feature ranking was done on the value of t value featureselection algorithm. Least squares support vector machine classifier was used to classify the image to findthe image with and without glaucoma. This approach boosts of 98.33% accuracy.

3. LITRATURE REVIEW

Annu, N., and Judith Justin et al., [2] in 2013 brought upa novel method for detection using DWT based textural energy features. Wavelet features are generated using five filters as specified in the paper. This system boosts of achieving 95% accuracy for detection.

In [3] Abhishek Pal et al., in 2018, proposed G-EYENET named auto encoding system which consists of two model system frame in which the ROI which is region ofinterest comprising of OD is obtained from fundus images. It was obtained with the help of modified u-net CNN comprising of binary map

In 2015, [4] Xiangyu Chen et al., proposed 6 layered CNN for glaucoma detection. Over fitting was a major problem which was taken care of by using responsenormalization andwith pooling layers. The system was known to use dropout and data augmentation strategies to improve performance.

In [5] Alan Carlos de Moura Lima, et al., in 2018, a comparison study is made between various CNNs to find out the best. A large number of features were extracted by each of CNN architecture since per image forming five datasets for each image.

In [6] U. Raghavendra et al., in 2015, used the source of energy spectrum for glaucoma detection. At first optic disc localization was performed by a search windowbased method. After that Radon transformation (RT) was performed followed by modified census transformation (MCT). SVM the classifier used. This method was known to claim the accuracy of ninety seven percent.

In [7] S. Maheshwari et al., in 2017 proposed a method for glaucoma diagnosis. At first EWT was used to image breakdown into various frequency bands. After that correntropy features were obtained. Then feature rankingwas done on the value of t value feature selection algorithm. Least squares support vector machine classifier was used to classify the image to find the imagewith and without glaucoma. This approach boosts of 98.33% accuracy.

In [8], 2017 authors formulated a glaucoma diagnosis using texton and local configuration pattern based features. Initially, adaptive histogram equalization was performed by them, followed by convolution operation of images with various filter Department of CSE (MCA), VTU‟s Center for PG Studies, Kalaburagi. 5 "Self- Organised Operational Neural Networks for Early Glacomua Diagnosis in Digital Fundus Images" banks, resulting in generation of textons. Further, Localconfiguration pattern (LCP) was generated which referred to distinctive pattern which was found in the image the system accuracy was 95.8%.

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4. METHODOLOGY

Data Collection and Preprocessing: Gather a diversedataset of digital fundus images containing both normaland glaucomatous cases. Preprocess the images to enhance quality, normalize illumination, and potentially augment the dataset to increase variability and robustness.

Feature Extraction: Unlike traditional methods that rely on manual feature extraction, Self-ONN is designed to autonomously learn relevant features directly from theimages. This step involves feeding preprocessed fundus images into the Self-ONN model, which automatically extracts and organizes features that are discriminative for distinguishing between normal and glaucomatous conditions.

Self-Organizing Neural Network Training: Train the Self-ONN model using the preprocessed and feature-extracted dataset. Self-ONN works by organizing its neurons in response to input data, forming clusters that represent different patterns present in the fundus images. During training, the network adjusts its weights to Department of CSE (MCA), VTU‟s Center for PG Studies, Kalaburagi. 3 "Self- Organised Operational Neural Networks for Early Glacomua Diagnosis in Digital Fundus Images" minimize classification errors and enhance its ability to detect glaucoma-related patterns.

2. **Real-Time Inference Pipeline**: Develop an optimized real-time inference pipeline that integrates the trained Self-ONN model. This pipeline should be capable of processing fundus images in real-time, extracting features on-the-fly, and making swift predictions regarding the presence of glaucomatous changes.
3. **Evaluation and Validation**: Evaluate the performance of the Self-ONN-based system using appropriate metrics such as accuracy, sensitivity, specificity, and computational efficiency. Compare the results with existing diagnostic methods and clinical standards to validate the effectiveness of the proposed approach in real-world scenarios.
4. **Iterative Improvement**: Iterate on the methodology based on evaluation results, potentially refining preprocessing techniques, adjusting model parameters, or exploring additional data augmentation strategies to further enhance performance and robustness.

4.3 ALGORITHAM

CNNs are the backbone of the system due to their abilityto automatically learn hierarchical features from images. Popular architectures such as VGG16, Resnet, and Inception are used for their proven effectiveness in image classification tasks. Pretrained CNN models on large datasets like ImageNet are fine-tuned on the animal skin disorder dataset. Transfer learning helps in leveraging pre-learned features, reducing the need for extensive training data and computational resources. To prevent overfitting and improve the robustness of the model, various data augmentation techniques are applied. These include random rotations, horizontal and vertical flips, brightness and contrast adjustments, and random cropping. Augmentation increases the diversityof the training data, helping the model generalize better. CNN layers are used to extract high-level features fromimages, which capture essential details such as texture, color, and shape of the lesions. These features are crucial for differentiating between various skin disorders. The final layer of the CNN uses a SoftMax activation function to output probability distributions over multiple classes, corresponding to different types of skin disorders. The class with the highest probability is chosen as the predicted diagnosis. To improve the robustness and accuracy of the system, ensemble learning techniques are employed. Multiple CNN models are trained and their predictions are combined (e.g., through majority voting or averaging) to produce the final diagnosis. these metrics are used to evaluate theperformance of the models. Accuracy measures the overall correctness of the predictions, while precision and recall provide insights into the model's ability to correctly identify true positives without producing falsepositives. The F1-score is the harmonic mean of precision and recall, providing a balanced evaluation metric.

5. CONCLUSION

This review tries to address different kinds of applications of deep learning methodologies in glaucoma diagnosis. Glaucoma is one of the crucial elements adding to the majority of visual impairment allaround. It is important to build up some modest computerized procedures for the exact discovery of various phases of glaucoma. These systems will be of bizarre assistance in underdeveloped nations where there is an intense lack of ophthalmologists. It is quite prominent from the survey that deep learning applications in retinal images are quite useful and effective. In this study, Self-ONNs are proposed to detect glaucoma disease from the acquired fundus images as an alternative to the commonly applied deep CNNs with high computational complexity and special hardware requirements. The proposed classifier achieved a significant performance gap of 8-12% F1 score over equivalent CNN and even deep CNN modelsfor the three benchmark glaucoma datasets. Deep CNNswith a large number of neurons and higher depths were outperformed by the proposed Self ONNs despite the fact that they were pre-trained and tuned for the classification problem at hand via transfer learning. Self-ONNs achieved the state-of-the-art performance levels in glaucoma detection with a reduced complexity compared to deep CNN models, and can hence be integrated into a decision support system for real-time glaucoma detection. Future work will focus on further improving Self ONN‟s classification performance by properly combining a segmentation network.

RESULTS

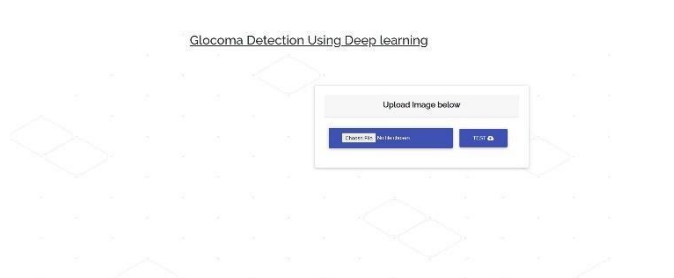

Figure 1 : Image uploading for glaucoma detection

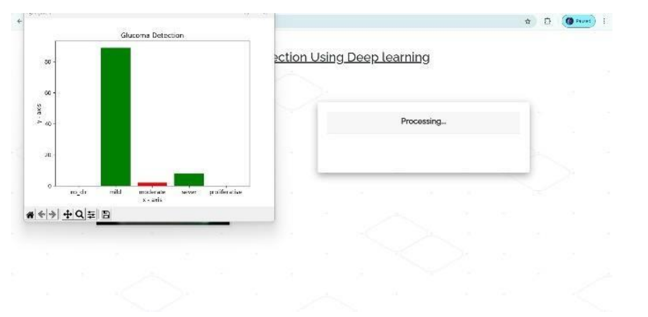

Figure 2 : Graph for glaucoma detection

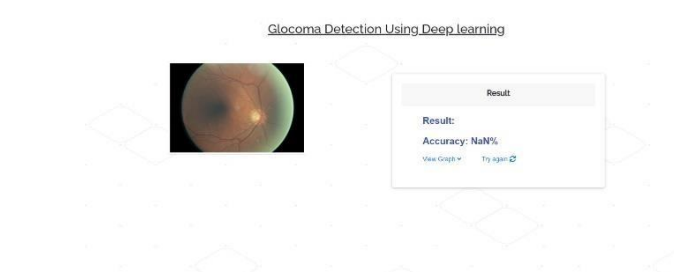

Figure 3 : Result with accuracy for glaucoma detection

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