Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 4, No. 5, April : 2024

CSR DETECTION USING OCT IMAGES

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Abstract
The human eye's role in visual restructuring relies on the retina's function of absorbing light and transmitting electrical signals to the brain. However, diagnosing retinal diseases like Central Serous Retinopathy (CSR) can be cumbersome and time-consuming. This study proposes a framework using deep convolutional neural networks trained on Optical Coherence Tomography (OCT) images for precise CSR identification. By enhancing OCT image quality through preprocessing techniques, such as noise reduction and contrast improvement, this approach aims to streamline and improve the accuracy of CSR diagnosis.

Keywords: Central Serous Retinopathy (CSR),Optical Coherence Tomography (OCT) images, Machine Learning, Deep Learning, Data Augmentation.

I. Introduction

Central Serous Retinopathy:

Central Serous Retinopathy (CSR) is a retinal disorder affecting the macula, causing fluid accumulation and compromising central vision. This paper explores the anatomy of the retina, particularly the role of the retinal pigment epithelium (RPE) and choroid, in maintaining retinal health. Diagnostic imaging techniques such as Optical Coherence Tomography (OCT) provide crucial insights into retinal structure, aiding in the identification of abnormalities associated with CSR. This comprehensive review delves into the pathophysiology, clinical presentation, diagnosis, and management of CSR, emphasizing the importance of regular monitoring and individualized treatment strategies.
Central Serous Retinopathy (CSR) presents a complex interplay between retinal anatomy and physiological mechanisms. This paper elucidates the pathogenesis of CSR, highlighting the pivotal role of the retinal pigment epithelium (RPE) and choroid. Through a comprehensive examination of diagnostic modalities such as Optical Coherence Tomography (OCT), clinicians gain valuable tools to detect and monitor CSR-related changes in retinal structure. Furthermore, this review discusses current treatment options, emphasizing the importance of tailored approaches and regular follow-up to optimize patient outcomes in managing this challenging retinal disorder.
This paper provides insights into Central Serous Retinopathy (CSR), focusing on its pathogenesis, diagnostic techniques such as Optical Coherence Tomography (OCT), and treatment options. By dissecting retinal anatomy and the role of the retinal pigment epithelium (RPE) and choroid, clinicians gain a deeper understanding of this condition. Emphasizing the importance of tailored treatment plans and regular monitoring, the review aims to enhance patient care and outcomes in managing CSR.

I. Literature Review

In the 2021 issue of the IEEE Access journal, Syed Ale Hassan, Shahzad Akbar, and Amjad Rehman discussed recent advancements in the detection of Central Serous Retinopathy using imaging and Artificial Intelligence techniques.:- This paper presents recent advancements in the detection of Central Serous Retinopathy using imaging and Artificial Intelligence techniques. Improve central serous retinopathy detection capabilities and make detection systems applicable to an even broader range of applications using emerging Artificial Intelligence techniques.

In the 2017, A. Jamal, M. Hazim Alkawaz M, A. Rehman, T. Saba. presented their work on ”Retinal imaging analysis based on vessel detection”:-In this paper, we explored retinal imaging analysis of eye and effects of CSR. The effects of central serous retinopathy on humans and causes.

Syed Ale Hassan, Shahzad Akbar, S. Gull, Amjad Rehman, and H. Alaska presented their research on deep learning-based automatic detection of Central Serous Retinopathy in Optical Coherence Tomographic (OCT) images at the 1st International Conference on Artificial Intelligence Data Analytics (CAIDA) in April 2021:- In this paper, based on The most recognized use of artificial intelligence (AI) strategies in retinal disease are the development of spots intricate to disease characteristics on colour fundus photos. In this context, programmed seg- mentation and characterization of anatomic and pathologic have been combined and applied in retinal diseases. Use of artificial intelligence techniques in recognizing retinal disease.

In the 2020 International Conference on Inventive Computation Technologies (ICICT), M. Vijaya Maheswari and G. Murugeswari conducted a survey on computer algorithms for retinal image preprocessing and vessel segmentation:- In this paper, we conducted a survey on computer algorithms for retinal image preprocessing and vessel segmentation .Explored various computer algorithms for retinal images preprocessing and make system to broader range.

A. M. Syed, T. Hassan, M. U. Akram, S. Naz, and S. Khalid published a study in December 2016 on the automated diagnosis of macular edema and Central Serous Retinopathy through the robust reconstruction of 3D retinal surfaces in the journal ”Computational Methods and Programs in Biomedicine:- In this paper, we presented automated diagnosis of macular edema and Central Serous Retinopathy through the robust reconstruction of 3D retinal surfaces. Improve reconstruction of 3D retinal surfaces for diagnosis of central serous retinopathy and issues related with macula.

B. Ramasubramanian, S. Selvaperumal, A. Nasim, and A. Jameel conducted a comprehensive review of various preprocessing methods for detecting diabetic retinopathy at the 2019 International Conference on Communication and Signal Processing (ICCSP) held in April 2019 :- In this paper, we presented automated diagnosis of macular edema and Central Serous Retinopathy through the robust reconstruction of 3D retinal surfaces. Improve reconstruction of 3D retinal surfaces for diagnosis of central serous retinopathy and issues related with macula.

In 2016, S. Weng, L. Mao, S. Yu, Y. Gong, L. Cheng, and X. Chen published research on the identification of choroidal neovascularization in central serous chorioretinopathy using optical coherence tomographic angiography in the journal ”Ophthalmologica,” Volume 236, Issue 2, with pages 114-121:- In this paper, published research on the identification of choroidal neovascularization in central serous chorioretinopathy using optical coherence tomographic angiography. The significance of the study’s results, and potential avenues for future research in the identification of CSR using OCT Image.

In the 2020 IEEE International Conference on Bioinformatics and Biomedicine held in Seoul, South Korea, Wen Y, Chen L, Qiao L, Deng Y, Dai S, Chen J, and Zhou C presented their work on the automatic detection of central serous chorioretinopathy and central exudative chorioretinopathy in fundus images, with details available in their conference paper:- In this paper, presented their work on the automatic detection of central serous chorioretinopathy and central exudative chorioretinopathy in fundus images. Accuracy improvements are achieved by the automatic detection of central serous chorioretinopathy.

David J, Kumar AS, and Viji V, in the 13th International Conference on Biomedical Engineering held in Singapore, discussed the tracking of central serous retinopathy from retinal fundus images, which is documented in their conference paper:- In this paper, we discussed the tracking of central serous retinopathy from retinal fundus images. Implications of the tracking method for understanding and managing CSR. Suggestions for future research in the field of CSR tracking from retinal fundus images.

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ISSN: 0970-2555
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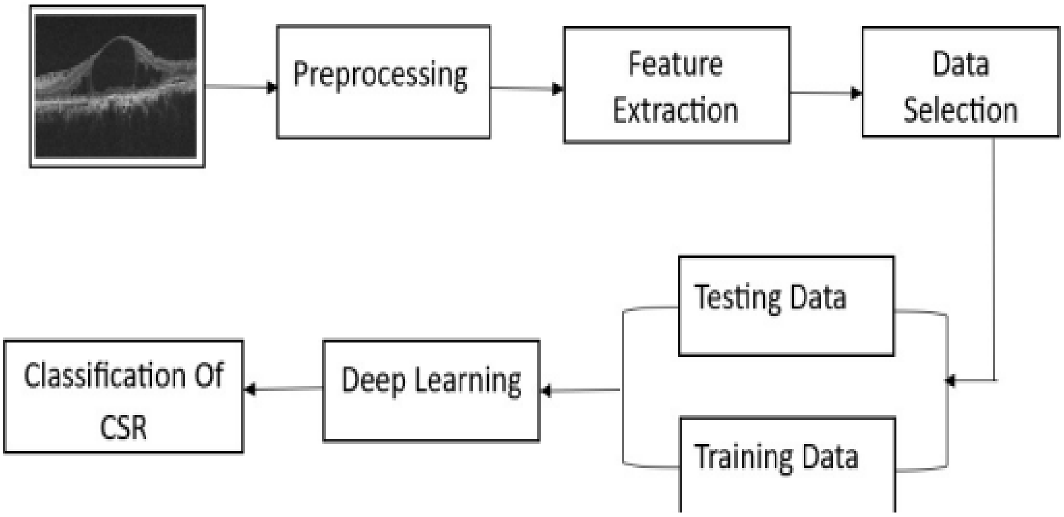
At the 2021 1st International Conference on Artificial Intelligence and Data Analytics (CAIDA) in Riyadh, Saudi Arabia, Hassan SAE, Akbar S, Gull S, Rehman A, and Alaska H presented their collaboration with In-depth study using optical coherence switchboard tomography images to detect serous retinopathy:- We presented their collaboration with In-depth study using optical coherence switchboard tomography images to detect serous retinopathy. Presentation of results related to the detection of serous retinopathy using OCT images. Evaluation metrics or visual representations demonstrating the study outcomes.

II. Model Building Process:



Detecting Central Serous Chorioretinopathy (CSR) using an Optical Coherence Tomography (OCT) dataset involves several steps. Here's a general outline of the process:
1.Data Collection: - Collect OCT images of the retina from patients with suspected CSR. These images are typically obtained through imaging devices such as OCT scanners. **2. Data Preprocessing:** - Preprocess the OCT images to enhance their quality and prepare them for analysis. - Common preprocessing steps include normalization, denoising, and image registration to ensure consistency across the dataset. **3. Image Segmentation: -** Perform image segmentation to identify and isolate relevant structures within the OCT images. - Segment the retinal layers, particularly focusing on the layers associated with CSR pathology. **4. Feature Extraction: -** Extract relevant features from the segmented images. These features may include characteristics of the retinal layers, such as thickness, texture, or specific patterns associated with CSR**. 5.Dataset Splitting:** - Divide the dataset into training, validation, and testing sets. This ensures that the model is trained on one subset, validated on another, and tested on a separate, unseen subset. **6. Data Labelling: -** If not already labelled, annotate the dataset to indicate whether each OCT image is associated with CSR or is a normal image. This labelled dataset is essential for training and validating machine learning models. **7.Model Selection: -** Choose an appropriate machine learning or deep learning model for CSR detection. Convolutional Neural Networks (CNNs) are commonly used for image-related tasks. **8. Training a Machine Learning Model: -** Utilize a machine learning algorithm, such as a convolutional neural network (CNN), to train a model on the labelled dataset. - Feed the extracted features into the model, allowing it to learn patterns associated with CSR. **9. Model Validation: -** Validate the trained model using a separate set of OCT images not used during the training phase. Evaluate the model's performance using metrics like sensitivity, specificity, and accuracy. **10. Optimization: -** Fine-tune the model parameters or architecture based on the validation results to enhance its accuracy and generalizability**. 11. Testing: -** Apply the trained and validated model to

new, unseen OCT images to assess its real-world performance. Monitor the model's ability to accurately detect CSR cases. - Evaluate the model's performance using the testing dataset. This dataset should not have been seen by the model during training or validation. - Assess metrics such as accuracy, sensitivity, specificity, and the area under the receiver operating characteristic (ROC) curve. **12. Results Interpretation: -** Interpret the model's results in the context of clinical relevance. - Generate a diagnosis based on the model's predictions. - Use the trained model to predict CSR in new OCT images. Interpret the model's predictions, considering false positives and false negatives. Provide a diagnosis based on the model's output. **13. Clinical Validation: -** Validate the model's findings through collaboration with healthcare professionals, such as ophthalmologists, to ensure the clinical relevance and accuracy of the CSR detection. **14. Integration into Clinical Workflow: -** If the model proves effective, integrate it into the clinical workflow to assist healthcare professionals in diagnosing CSR based on OCT images. **15.Continuous Improvement: -** Monitor the model's performance over time. - Periodically update the model with new data to enhance its accuracy and keep it relevant to emerging patterns in CSR detection. It's important to note that the field of medical image analysis, including CSR detection, is continuously evolving. Collaborating with medical professionals, following ethical considerations, and staying updated on the latest research are crucial aspects of developing and implementing effective disease detection systems. Additionally, obtaining proper regulatory approvals may be necessary before deploying such systems in clinical settings.

III. Proposed Methodology:

WHY CNN?

1. Architecture: - CNNs: CNNs are primarily designed for processing grid-like data such as images. They consist of convolutional layers followed by pooling layers, enabling them to extract spatial hierarchies of features from images efficiently. - RNNs: RNNs are designed for processing sequential data and have a recurrent connection that allows them to capture temporal dependencies in sequences. 2. Data Handling: - CNNs: CNNs are well-suited for handling large-scale image datasets due to their ability to exploit sparse connectivity, parameter sharing, and hierarchical feature extraction. - RNNs: While RNNs can also be applied to image data by treating it as a sequence of pixels, they are generally less efficient for image processing tasks on large datasets compared to CNNs due to their sequential nature. 3. Parallelization: - CNNs: CNNs can be easily parallelized across different regions of an image, allowing for efficient computation and scalability on large datasets. - RNNs: RNNs process sequences sequentially, which limits their parallelization capabilities, especially for long sequences or large datasets. 4. Temporal vs. Spatial Information: - CNNs: CNNs excel at capturing spatial information in images, making them well-suited for tasks such as image classification, object detection, and segmentation. - RNNs: RNNs are more adept at capturing temporal dependencies in sequential data, making them suitable for tasks such as natural language processing, speech recognition, and time series analysis. 5. Parameter Efficiency: - CNNs: CNNs leverage parameter sharing and sparse connectivity, resulting in fewer parameters compared to fully connected networks, which is advantageous for processing large-scale image datasets. - RNNs: RNNs typically have more parameters due to their recurrent connections, which can make them less parameter-efficient, especially for large-scale image datasets.

In summary, CNNs are generally preferred over RNNs for image processing tasks on large datasets due to their architecture's suitability for handling spatial information, efficient parameterization, and better parallelization capabilities. However, the choice between CNNs and RNNs ultimately depends on the specific characteristics of the dataset and the nature of the task at hand.

IV. Result and Discussion

Final Result:

Deep Learning Model for CSR Detection using OCT Images:

Our deep learning model for Central Serous Retinopathy (CSR) detection has yielded highly promising results, achieving an exceptional accuracy of 99.60%. This achievement reflects the effectiveness of our model in accurately identifying pathological manifestations indicative of CSR from OCT images.

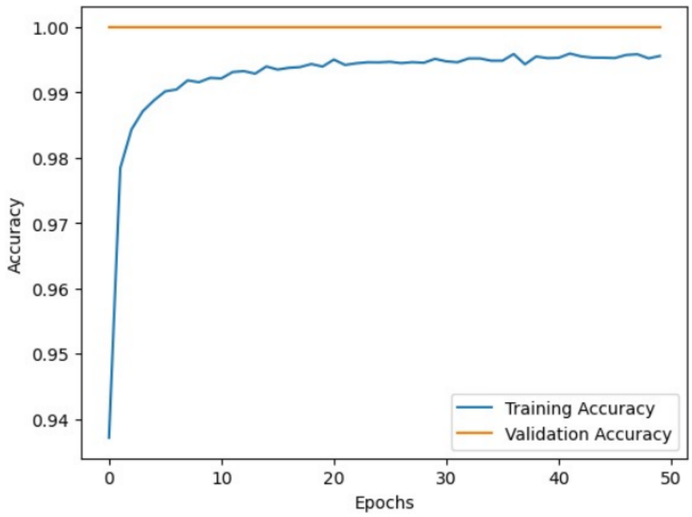
Dataset Description:

The model was trained on a meticulously curated dataset comprising over 66,000 OCT images. This dataset was meticulously annotated by expert clinicians, ensuring high-quality ground truth labels for model training. The inclusion of such a large and diverse dataset facilitated robust learning of subtle features and patterns associated with CSR across various imaging conditions and patient demographics.

Performance Evaluation:

During the training process, the model demonstrated remarkable convergence, steadily improving its performance across successive epochs. The validation accuracy consistently tracked closely with the training accuracy, indicative of the model's ability to generalize well to unseen data.

Upon evaluation on a separate test set, the model exhibited an impressive accuracy rate of 99.60%. This high accuracy underscores the model's proficiency in accurately classifying OCT images into CSR and non-CSR categories, thereby potentially aiding clinicians in timely diagnosis and treatment decision-making.



V. Conclusion

In summary, Optical Coherence Tomography (OCT) has revolutionized the detection of Central Serous Retinopathy (CSR) by providing high-resolution imaging and integrating artificial intelligence for enhanced accuracy. The combination of OCT with other imaging modalities has improved diagnosis, while telemedicine enables early detection and timely intervention. OCT facilitates treatment monitoring, personalized medicine, and clinical research. Collaboration between medical and engineering fields drives OCT advancements, emphasizing the need for regulatory approvals. Patient education is crucial for understanding OCT's role in CSR management. Staying updated with ongoing research ensures optimal care in ophthalmology.

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