SVM based CSR disease detection for OCT and Fundus Imaging

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Abstract — ***CSR is a retinal disease that affects vision and causes blindness. The CSR is brought on by an accumulation of watery fluid behind the retina. The early detection and treatment of CSR disease enables the avoidance and cure of eye damage. Retinal diseases include glaucoma, Drusen, and diabetic retinopathy (DR), as well as Central Serous Retinopathy (CSR), Choroidal Neovascularization (CNV), Age-Related Macular Degeneration (AMD), Diabetic Macula Edema (DME), and Age-Related Macular Atrophy (ARMA). Several cutting-edge methods and research assist the automatic identification of CSR. Two imaging techniques were employed to identify CSR disease. The two imaging or scanning (dataset) methods used are optical coherence tomography (OCT) angiography and fundus imaging. The novel based technology used in this work provides automatic CSR detection. A Support Vector Machine (SVM) is used to categorize and identify CSR disease. The findings after implementation are examined and presented.***

Keywords - Support Vector Machine (SVM), Central Serous Retinopathy (CSR), OCT imaging and Fundus imaging.

1. INTRODUCTION

Retina is a thin layer which is made up of sensitive tissues that is located beneath the eyeball, near to the optic nerve. It takes the concentrated light signals which comes from eye lens, transforms to neural impulses, and then transmits those signals to the brain, so that brain can interpret the images. The anatomy of the retina and an overview of the most prevalent retinal diseases, including glaucoma, cardiovascular disease, AMD, CNV, and CSR, DR, and DME, are provided in this section. The following section covers the imaging techniques used for classifying and detect retinal diseases. This study is interested in CSR disease.

1.1 Structure of the Eye

The regions of the human eye that are most easily identified are the sclera, cornea, iris, and pupil. The internal surface is made up of the retina, macular, fovea, optic disc, and posterior pole, as depicted in Fig. 1. When we gaze at something, light enters our eyes through the cornea, where it partially concentrates the image before reaching the pupil and lens. The image is further strengthened by the lens. After passing through the vitreous, the picture is focused on the macula, a portion of the central retina [12]. For tasks like reading, writing, and colour discrimination, humans can perceive fine detail thanks to this specialized area of the retina. The second half of the retina, known as the peripheral retina, regulates side vision. The retina, a layer of tissue in the eye, converts light that enters into a neural signal that is then sent to the brain for additional processing [13]. As a result, the retina serves as a brain extension. A web of blood arteries supplies the retina with blood. For instance, diabetes has the ability to harm the retina's blood vessels and impair its functionality.

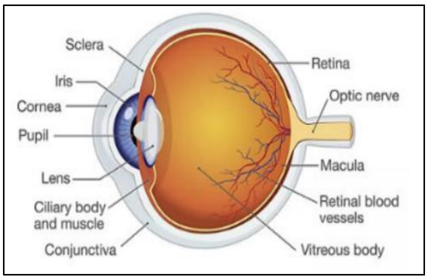

Fig. 1: schematic of human eye

Using imaging techniques including fundus photography, auto-fluorescence (AF), optical coherence tomography (OCT) and angiography, one may diagnose retinal retina and identify CSR diseases. In more recent Deep Learning (DL) studies, each patient are potential source of priceless diagnostic information that would be utilized to train current Machine Learning (ML) models to obtain improved treatment and diagnosis. The creation of marks and changes in the layers are the disease features on coloured fundus scan image are most common features that are used by AIML methods in retinal disease Detection. The implementation and acceptance of the OCT approach has allowed for the efficient use of these techniques. Because of this, automatic fractioning of retinal pathology, intraretinal fluid, colour epithelial disintegration, drusen and topographical atrophy, may now be carried out with the same standard as manually done by human. Another area of study is creating a profoundly settled picture of retinal vasculature utilising OCT scans to produce several successively created images. The identification of retinal diseases such “diabetic retinopathy”, “hypertensive retinopathy”, “age-related macular degeneration”, and glaucoma have recently benefited from the development of various automated techniques. Clinical systems now often use the automated detection and diagnosis of retinal illnesses through the evaluation of retinal pictures. These automated methods give the doctors more precise and optimal outcomes.

Until recently, detection of retina related diseases required labour-intensive, incorrect, and wasteful manual approaches. In contrast, computer-aided retinal disease identification systems are quick, simple, accurate, and cost-effective. Additionally, they don't rely much on an expert ophthalmologist's capacity to recognise the disease from different scanned pictures. This review research is focused on specific retinal disease called “central serous retinopathy” (CSR) or “central serous chorioretinopathy” (CSC). Fig. 2 depicts a fundus camera image of a normal retina.

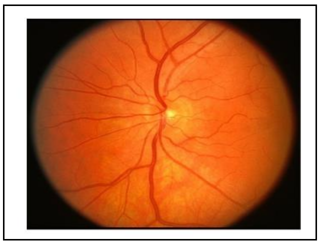

Fig. 2: Retinal normal view

1.2 About CSR disease

CSR is most common disease now a days. this disease causes by an accumulation of fluid beneath the retina, it can seriously impair vision owing to the retina's thin tissue layer. As a result, early identification effectively makes it possible to take the necessary precautions to regain vision, which results in full recovery. According to studies, CSR often affects single eye, although it is possible that may damage both eyes. In other instances, patients may also heal without any therapy after some period of time. With severe CSR, a patient may have vision obscuration, may result in metamorphopsia, slight hyperopia, contrast sensitivity, and shading vision.

The focal retina typically has central serous separation, occasionally with dull yellow stores, and rarely with a serous RPE separation, in certain CSR instances, a sub-retinal fluid accumulation persists for three months or longer, causing long-term visual problems. Sub-retinal fluid levels fluctuate regularly in situations with CSR like this, majority of the patients will recover early. According to historical statistics, up to half of CSR patients may face relapses of the condition within one year, necessitating the patient to undertake variety of therapeutic procedures that might last up to few months in patients with chronic CSR, first-time CSR and recurrent CSR. Fig. 3 shows the visual difference for healthy eye vision and CSR affected vision.

Fig. 3: Healthy eye vision and CSR affected vision

The objective of this work is to build appropriate model to detect CSR disease. The accuracy of SVM algorithm is better as compared to other algorithms. This paper is organized as section I describes the introduction of the proposed system, section II describes the literature survey done for this work, section III describes about research methodology used in this work, section IV describes result and discussions, section V describes conclusion of the proposed work.

2. LITEREATURE REVIEW

Studies and research on the CSR disease are outlined and developed in the literature review. Based on established criteria for automatic CSR detection, a large number of pertinent and related CSR papers and publications were selected for study and evaluation. Various cutting-edge CSR detection techniques based on AIML and DL were selected for analysis in this research. The author [1] proposed a survey paper on all recent publications and developments based on the classification, detection of CSR disease using AIML and Deep Learning methods, using both the imaging technics. The author recommends that the recent AIML and deep leaning methods gives more prominent results. The author [2] proposed a way for an automated system for Central Serous Retinopathy (CSR) disease diagnosis utilizing Deep SVM for OCT scan images. Here, the author only worked on OCT imaging, our work also involved a comparison of fundus images. According to author [3], who presented Capsule network-based designs, the created approach outperformed UNet architecture and used less training parameters. The author [4] presented "Indo Cyanine Green Angiography" (ICGA) and acute CSR and different OCT angiography characteristics along with the difference in accuracy. One of the retinal diseases called "Macular Edoema" (ME) was suggested by the author [5] in a review paper on OCT and fundus images.

In the year 2020, author [6] offered a rational solution to CSR detection issues. Three steps make up the process. The initial phase requires the comprehensive reconstruction of the 3-D OCT retinal surface, and the second phase entails the creation of two feature sets, one for cyst fluid and the other for thickness profile. The topic of the retina is categorized using the SVM classifier algorithm. The lodged method used multiple OCT photos for the identification of CSR whereas various researchers experimented with OCT, fundus photographs. Author [7] proposed a decision support system, was published in 2019, and made a clumsy attempt to identify CSR from retinal images using an SVM classifier. Before segmentation is applied, the input image is sparsely de-noised. From the retinal layers created by this segmentation, a profile of retinal thickness is produced. SVM classifier was employed in this study. In the work "Multi-Disease Detection in Retinal Imaging Based on Assembling Heterogeneous Deep Learning Models" published in German Medical Data Sciences 2021, Author [9] suggested that employing heterogeneous deep learning models can produce better outcomes.

3. RESEARCH METHEDOLOGY

3.1 Proposed Work Flow

The workflow briefs about progress of process and how the system behaves for the boundary environments. The Workflow diagram and flow of data are depicted in fig. 4, the figure describes how process progresses in entire work.

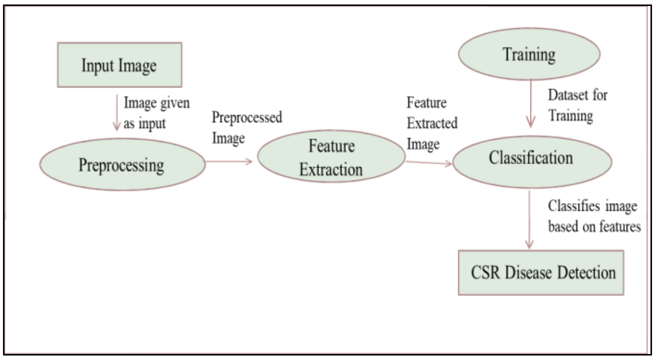

Fig. 4: Dataflow diagram of proposed system

The first step in this process is to provide an input of a retinal picture, which is then preprocessed to identify for any errors or improve visualization for the next steps. Following preprocessing, the eye scan's numerous components and characteristics are retrieved during the feature extraction step. The dataset is then segmented into separate subset for training or testing process. The suitable model is built and the algorithmic model learns to identify any CSR diseases in given input images after analyzing hundreds of images.

The architecture diagram provides an overview of an entire system, identifying the main components and interfaces that are used for the purpose. Fig. 5 demonstrates the architecture diagram for the proposed system. Design explains the architecture components that are used for developing a software product.

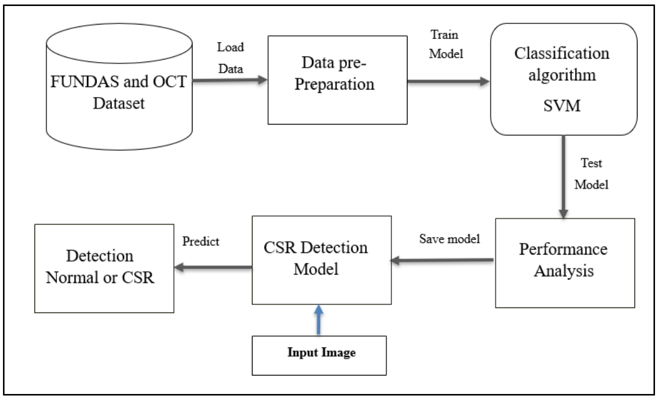

Fig. 5: System Architecture of proposed system.

This model takes the input as two type of dataset OCT dataset and Fundus dataset of retinal images, these images are preprocessed using some pre-processing technics for better visualization. After preprocessing the suitable model is built by optimizing several parameters and increasing the epochs using SVM algorithm. Performance is analyzed and presented in performance section. research work. We briefly discuss two publicly accessible datasets.

3.2 Overview of Retinal Imaging dataset

Two publicly accessible CSR-related datasets were used and examined in this paper. These datasets are collection of OCT, fundus photos. These available datasets were used by numerous researchers and may be easily downloaded using their unique URLs. To accomplish testing objectives and train Machine Learning models, a fraction of the full-on images from these datasets are used in experimental

1) Oct Dataset: It is non-invasive imaging method that used to capture 3-D volumetric photographs, and it has emerged as the most preferred method for examining the retinal anatomy. The retina's cross-section picture is recorded using waves. By using OCT scans, the eye expert can diagnose of the retina's many layers and determine the thickness each layer.

The labelled OCT pictures is found in Zhang's lab and also available in an OCT imaging database on the website of the “University of Waterloo” in Canada, this is opensource repository of OCT dataset. OCT image databases are widely accessible. It has been especially mentioned in relation to using image-based deep learning for medical diagnoses and curable diseases. For the purpose of experiments, we used 340 OCT images.

2) Fundus Dataset: The "fundus photography" approach of acquiring the retinal red-free image is considered as an alternative for OCT imaging. Fundus imaging is a two-dimensional (2-D) depiction of the three-dimensional retinal tissues cast onto the imaging surface. This is accomplished by the use of reflected light, with the amount of light reflected from the retinal tissue directly related to the picture intensity on the 2-D projection. This technology works based on color photographic film and the statistical methodology. Similar to this, digital representation of retina offers a fast, towering-resolution, and consistent image that is instantaneously available and managed for the creation of an image. Additionally, fundus photography is frequently used for clinical examinations and disease records, with the possibility for telemedicine and tolerant training. The photos produced by Fundus methods can also include ordinary and extended perspectives.

3.3 Splitting of dataset

Dataset is divided into two parts Train Data, Test Data using the built-in library known as “sklearn”.

3) Training Data: A for this work uses 80% of the original dataset and this numbers may vary depending on the needs of the experiment. This data is used to train the model, which tries to learn from the labeled dataset. Both the input and the predicted result are included in the training data.

4) Test Data: The test dataset is 20% of the original dataset and used to evaluate the model. It is used for the model’s evaluation process after it is fully trained.

3.4 Data Pre-preparation

Two publicly accessible CSR-related datasets are examined in this article. These CSR databases are the consists of OCT and fundus images, and a typical dataset constitute of a variety of records. These freely available datasets typically used and accessed by many academics, and may be quickly found using their unique connections. Data pre-preparation is carried out as seen in fig. 6, figure shows the image transformation from the original to the transformed image.

The preprocessing stage in our proposed system consists of four main phases, namely noise removal, gray-scale conversion, median filtering, and data transformation. Data transformation consists of five image transformation steps such as “random horizontal flip”, “random rotation”, “random resizing”, “transforming to tensor” and normalizing the data. Image preprocessing flow is as shown in fig. 6.

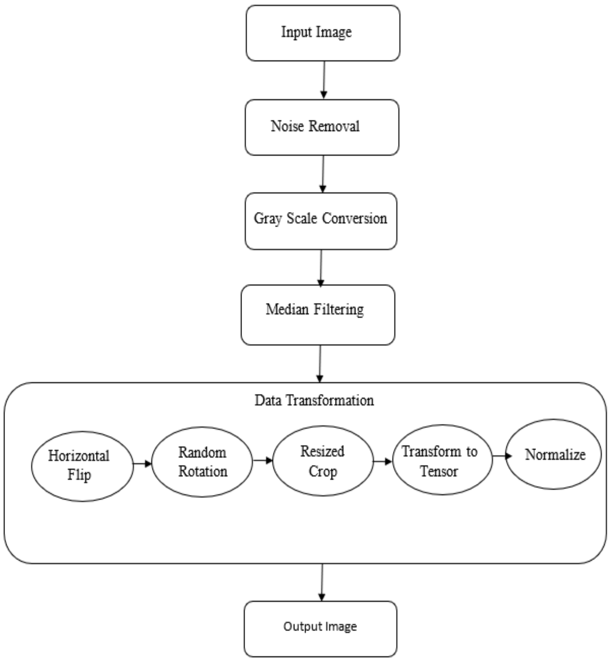

Fig. 6: Flow Diagram for Data pre-processing process

3.5 Classification

The primary objective of this initial batch of results is to identify any CSR grade. OCT and the Fundus dataset were used for it. With all the characteristics of these images, we trained an SVM classifier. The performance was also enhanced by choosing the SVM parameters and characteristics that were the most pertinent. Thus, a linear kernel function in the SVM technique was used to achieve the best accuracy for our detection. The results section displays the confusion matrix for the best detector. Tables 1 and 2 list the OCT and Fundus Dataset's accuracy, precision, and recall for proposed system.

3.6 Performance Measurement

In this proposed system we utilized five different metrics to measure the performance namely accuracy, precision, recall, f1_score which are defined as below equation 1, equation 2, equation 3, equation 4.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} X\ 100 \quad \text{----------------------- (1)}$$

$$Recall = \frac{TP}{TP+FN} \quad \text{----------------------- (2)}$$

$$Precision = \frac{TP}{TP+FP} \quad \text{----------------------- (3)}$$

$$F1\_Score = \frac{2\ X\ Recall\ X\ Precision}{Recall+Precision} \quad \text{----------------------- (4)}$$

where FP, FN, TP, TN stand for false positive, false negative, true positive and true negative, respectively. f denotes the predictor (model). Each group of classes is examined independently for FP, FN, TP and TN.

4. RESULT AND DISCUSSIONS

The proposed work is implemented using Python language and Streamlit framework which is open source, Streamlit helps in fastest building and sharing the machine learning web applications, it is an Python based library. We ran this experiment in local system with a Core i5 processor with 8GB RAM.

The obtained result of OCT images dataset using SVM classification algorithms against the measurement metrics accuracy, precision, recall, f1_score are as displayed in the table1.

Table1: Performance analysis for OCT images dataset

Metrics	Performance
accuracy	0.91
precision	0.77
recall	0.69
F1_score	0.70

In the same way obtained result of Fundus images dataset using SVM classification algorithms against the measurement metrics accuracy, precision, recall, f1_score are as displayed in the table2. We observe that this algorithm performs good for both input dataset.

Table2: Performance analysis for Fundus images dataset

Metrics	Performance
accuracy	0.90
precision	0.83
recall	0.79
F1_score	0.86

Performance analysis is done for both OCT images dataset and Fundus image dataset while implementation of this work. The output obtained from performance result is as displayed in the below graph in the fig. 7, figure depicts the graph against the parameters epochs vs loss, graph implemented to show training loss and validation loss, we observe that training loss has been reduced drastically.

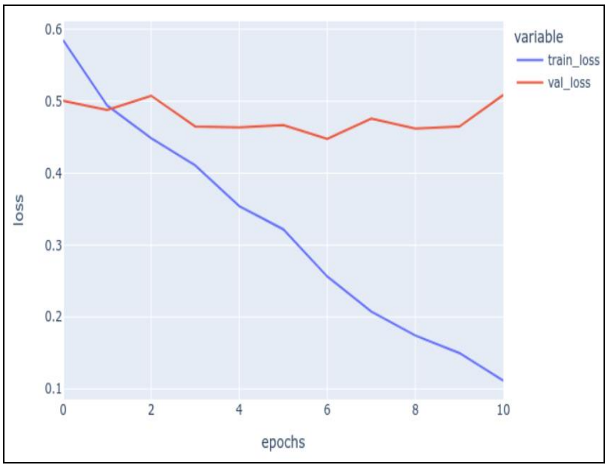

Fig. 7: Validation and Training Loss analysis for OCT dataset

Algorithm is implemented and performance is measured. SVM performance is using performance metrics, It is observed that the algorithm reached accuracy up to 91%.

5. CONCLUSION

The automated identification of CSR is supported by a number of innovative methods and studies. It was found that ML and DL techniques will enhance CSR analysis and detection. The OCT dataset and the Fundus dataset are used as inputs in this work. The Support Vector Machine (SVM) is applied for classification, this approach excels at identifying CSR diseases. Since it provides results with a 91% accuracy rate, it appears to be the one among most effective method for detecting CSR disease.

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