An Approach to the Detection of Retinoblastoma based on Apriori Algorithm

Pradeep Kumar K G
Department of Computer Science & Engineering
VTURRC, Belagavi
Belagavi, India
pradeepsdmit@gmail.com

Dr. Karunakara K
Department of Information Science & Engineering
SSIT, Tumakuru
Tumakuru, India
karunakarak@gmail.com

Dr. Thyagaraju G S
Department of Computer Science & Engineering
SDM Institute of Technology
Ujire, India
thyagaraju.gulasinda@gmail.com

Abstract—Retinoblastoma is a rare kind of cancer, typically designated as leukocoria (white-eye pupillary reflex) that rapidly develops from the immature cells of a retina, the light-detecting tissue of the eye. It is the most common malignant cancer of the eye in young children. Early detection of leukocoria can improve the overall treatment duration.There is intensification in interest for setting up medical system that can monitor a large number of people for sight threatening diseases, likely Retinoblastoma and Diabetic Retinopathy.Developed an image processing application for the discovery of retinoblastoma by exploiting graph theory based apriori algorithm as a novel approach and different image processing techniques.The application will review the image with different phases and identifies region of interest of the threatened area in the retina.The software is implemented using MATLAB and developed a graphical user interface for smooth proceedings during identification stages of the disease.

Keywords*-Retina, Retinoblastoma, Segmentation, Apriori algorithm, Canny edge detection*

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I. INTRODUCTION

Retinoblastoma (Rb) is an exceptional form of cancer that rapidly develops from the immature cells of a retina, the light-detecting tissue of the eye. It is the utmost usual malignant cancer of one eye or both in young children. The very regular and noticeable indication of retinoblastoma is an anomalous appearance of the retina as viewed through the pupil, the medical phrase for which is leukocoria, also known as amaurotic cat's eye reflex. The occurrence of the photographic fault red eye in only one eye and not in the other may be a symptom of retinoblastoma. A clearer indication is "white eye" or "cat's eye". It falls under two categories: (1) a genetic, inheritable form and (2) a non-genetic, non-heritable form. The symptoms are infrequent. Indications include: (1) a white color in the center circle of the eye (pupil) when light is shone in the eye, such as when taking a flash photograph. (2) Eyes that appear to be looking in different directions. (3) Eye redness. And (3) Eye swelling. Fig. 1 depicts anatomy of human eye with various regions.According to the surveys, in two thirds of instances, only one eye is affected (unilateral retinoblastoma). Although there are cases tumours seems to develop in both eyes (bilateral retinoblastoma). The quantity and dimension of tumours on every eye may differ. The location, dimension and amount of tumours are considered when selecting the type of treatment for the disease.

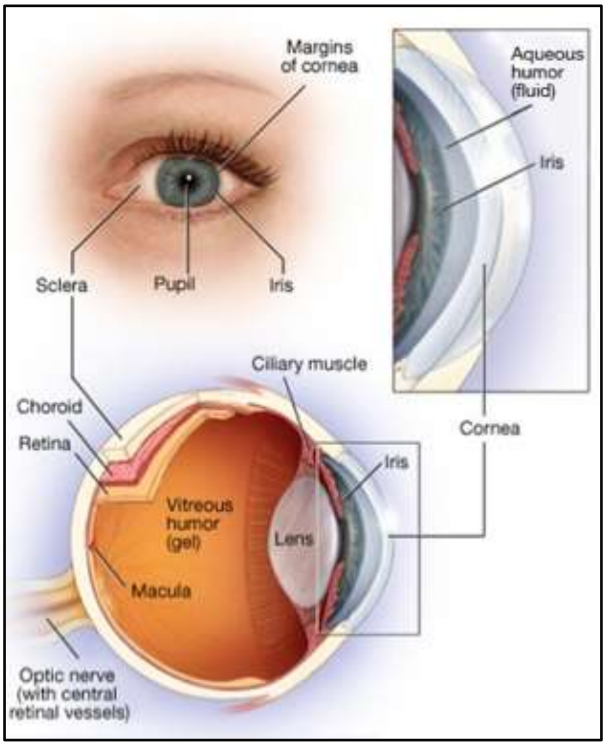

Figure 1. Anatomy of human eye

Certain children with retinoblastoma can acquire a squint, normally denoted as cross-eyed or wall-eyed (strabismus). Conversely, retinoblastoma occurrence with advanced disease in emerging countries and eye enlargement is a common finding [16]. The significance of retinoblastoma treatment is to protect the life of the child, then to preserve vision, and afterwards to minimize impediments or side effects of treatment. Roughly 80% of children with retinoblastoma are spotted before 3 years of age and diagnosis in children beyond 6 years of age is enormously rare [17].

Fundus photographs are ocular documentation that records the appearance of a patient's retina. The photographs allow the clinician to study a patient's retina, detect retinal changes and review a patient's retinal findings. Fig. 2 and Fig. 3 are the fundus images of human eye, normal and retinoblastoma affected eye respectively. Canny edge detector performed well as the portion is highlighted, so that opthalmologists can recognize about the stages of retinoblastoma by examining the results. Inspired by data mining and its apriori algorithm, which is used for identification purpose. The edge-detected image is then feed to the algorithm. The algorithm is the combination of graph theoretic concept, i.e., breadth first search and data-structure concept hash-tree structure. At first it searches for frequent patterns and stored in the data-structure as a hash tree. Every pattern from each dataset is compared and visualized for the region of interest.

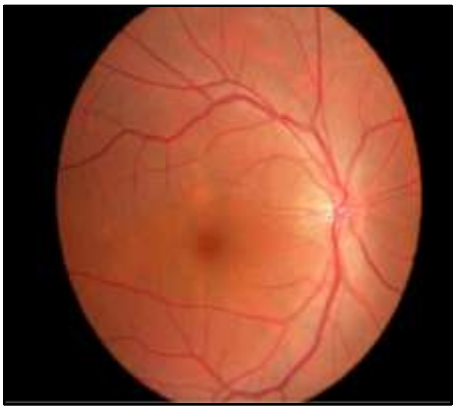

Figure 2. Fundus Image of an Normal eye

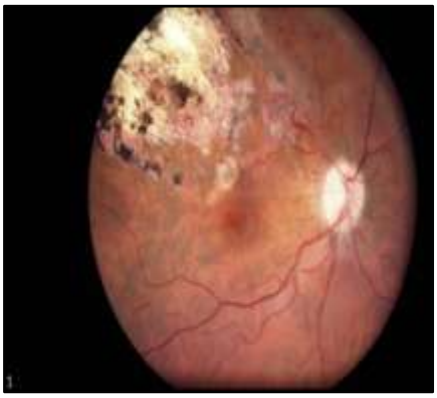

Figure 3. Fundus Image of an Retinoblastoma eye

II. LITERATURE SURVEY

A brief analysis about retinoblastoma and its features, previous findings, research is studied related to this work.Ryan Henning, Pablo Rivas Perea, Bryan Shawand Greg Hamerly demonstrated that, it is possible to detect leukocoria in raw digital images of cropped eyes by training convolutional neural networks. They trained numerous networks for the task, using training images downloaded from Flickr. Accomplished low error rates (<3%) for classification of eye images into three classes: normal, leukocoric, and pseudo-leukocoric.

Kenneth W. Tobin, Edward Chaum, V. Priya Govindasamy, and Thomas P. Karnowskiproposed a method trusts on the particular segmentation of the vasculature of the retina tailed by the determination of spatial structures the concentration, average thickness, and average orientation of the vasculature associated with the position of the optic nerve. Localization of the macula is formed to notice the horizontal raphe of the retina spending a geometric model of the vasculature. Reported 90.4% detection performance for the optic nerve and 92.5% localization performance for the macula by illustrating a number of 345 images conforming to 269 patients with 18 diverse pathologies.

Hong Shen, Charles V. Stewart, Badrinath Roysam, Gang Lin, and Howard L. Tanenbaum described an algorithm to continually and accurately assess the absolute location of a diagnostic or surgical tool pointed at the human retina, from a sequence of image frames. The method has accomplished 100 percent on 1024x1024 retina images. But the median registration error in any case is approximately 1 pixel.

Adam Hoover and Michael Goldbaum described a fuzzy convergence to determine the origination of the blood vessel method to locate the optic nerve in images of the ocular fundus. Evaluated with 31 images of healthy retinas and 50 images of diseased retinas in green band channel, achieved 89% correct detection.

Thomas Walter, Jean-Claude Klein, Pascale Massin, and Frederic Zana used mathematical morphology and applied to 1300x1024x8 angiographic images taken on a Topcon retinograph at the capillary time of the fluorescein diffusion. Extracted the vascular tree from the two images and detected the bifurcation points of the vessels. Then the two sets of points are matched by a bayesian hough transform and finally an affine transformation is determined in an iterative process and they proved to be appropriated to the problem of detection of microaneurysms.

Isabel N. Figueiredo, Susana Moura, Julio S. Neves, Luis Pinto, Sunil Kumar, Carlos M. Oliveira and Joao D. Ramos proposed a method for identifying individuals based on retinal fundus image matching. The method is based on the image registration of retina blood vessels. The method is tested on a data set of 21 721 real pairs generated from a total of 946 retinal fundus images of 339 different individuals, consisting of patients followed in the context of different retinal diseases and also healthy patients. The evaluation of its performance reveals that it achieves a very low false rejection rate (FRR) at zero FAR (the false acceptance rate), equal to 0.084, as well as a low equal error rate (EER), equal to 0.053. But concerns on the computational time, the average execution time.

Ishmeet Kaurand Lalit Mann Singh presented the approach of blood vessel segmentation. The image is analyzed and the result attained is, whether the image is diseased or not. The segmentation approach produced the accuracy of 98.7% while the diseased image was discovered with 99% accuracy. The procedure of segmentation of blood vessels involved image pre-processing, unsupervised approach and image post-processing.

R. Arunkumar andP. Karthigaikumar presented the retina based disease diagnosis through deep learning based feature extraction method with multi-class SVM classifier is used. Resulting in the process of reducing the system requirement and good performance.

Ibrahim Al Nawaiseh, Aseel Q. Ghanem, and Yacoub A. Yousef studied the impact of awareness of retinoblastoma in the affected families. This is a reflective, clinical case series of 44 patients with familial retinoblastoma. Out of 200 retinoblastoma patients, 44 (22%) patients survived ancestral, 18 were probands, and 26 were second, third, or fourth affected family participants. There were 76 affected eyes: 31 eyes of probands and 45 eyes of the supplementary affected family members. Patients diagnosed by screening (38%) had admirable visual outcome, and both eyes were recovered. Concluded by saying consciousness of families of the occasion of retinoblastoma and adequate screening steered to a significantly higher rate of eye salvage in patients with familial retinoblastoma.

James Boer and Gregory J. Hamerlydeveloped an easily maintainable and extensible system that can train hundreds of semi-random convolutional neural networks. Docker is used to enable simple and platform-agnostic deployment of the system. The Torch machine-learning library is used to train the convolutional neural networks. Training results are promising, with single-network performance at 96.6% using minimal data and 99.5% using data augmentation.

Bela S. Purohit, Maria Isabel Vargas, Angeliki Ailianou, Laura Merlini, Pierre Alexandre Poletti, Alexandra Platon, Benedicte M. Delattre, Olivier Rager, Karim Burkhardt and Minerva Becker spent attentiveness ondistribution weighted imaging, diffusion tensor imaging, fluoro-2-deoxy-D-glucose positron emission tomography CT, and positron emission tomography MRI. Learnt that, almost 90 % of cases happen less than 5 years of age, in a hereditary form (40 %) or in a sporadic form (60 %).

R.Ravindraiah, Dr. M.N.Giri Prasad, Fahimuddin.Shaik and E.Sreenivasulu used spatial domain filtering, edges are colored with unique color from other regions as pathologies are characterized by distinct color from the other regions. Designed a 2-dimensional filter of a specified type of edge operations, the magnitude of the resultant gradient image attained gives quite optimum results.

Pablo Rivas-Perea, Ryan Henning, Bryan Shaw and Greg Hamerly proposed an image-processing procedure for detecting the particular location and radius of the smallest circle containing the iris in an eye image. Used median filters and 2-dimensional stationary wavelet transforms in implementation, and achieved low error rates and sensitivity.

Michal Sofka and Charles V. Stewart combined matched filter and vessel boundary portions. The detailed training technique is employed to develop a mapping of this vector to measure the vesselness at each pixel. Results showed substantial improvements, both qualitatively and quantitatively and benefitted in efficient and effective vessel centerline extraction.

Richard Sharpit, Randall Ridgway, Kishore Mosaliganti, Okan Irfanoglu, Pamela Wenzel, Raghu Machiraju, Alain de Bruin, Gustavo Leone, Tony Pan, Kun Huang and Joel Saltz examined phenotype differences in wildtype and retinoblastoma knockout specimens of mouse placenta. Combined non-trivial registration techniques, an N-point correlation classifier, and a volume rendering step. Results showed average performance.

III. METHODOLOGY

An application is developed, which is capable of detecting affected retinoblastoma. Incorporated canny edge detection with apriori based algorithm [19]. Fig. 4 shows different phases incorporated in the development of application.

ISSN: 2321-8169
733 – 738

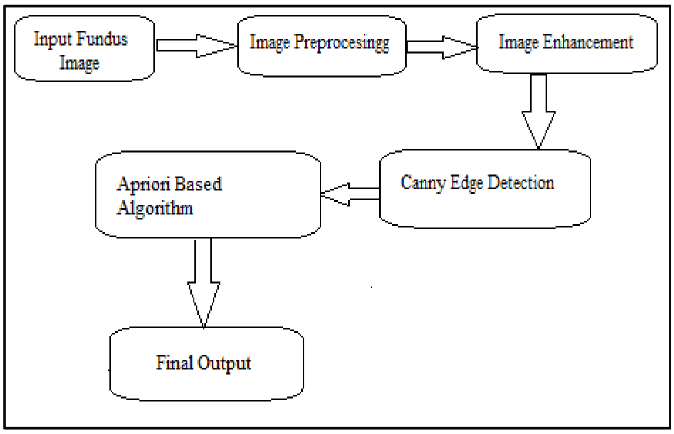

Figure 4: Phases adopted in the experiment

In phase 1, the fundus eye image that captured using fundus camera is given as input. In second stage, the image pre-processing is necessary to deepen the contrast of the images to provide a better transform representation for subsequent image analysis.Image pre-processing will be done in two stages in first, input image will be pre-processed in space domain for smoothing and in second phase the image is sharpened frequency domain. It is beneficial to consider a certain amount of image smoothing before the actual steps of detection. Image enhancement is performed in third phase. For visual investigation it demands a large amount of pixels and acceptable pixel depth so that the image can be attained with sufficient information to accomplish the iteration or further operations and subsequently display the result in detail for the viewer. For the enhanced image canny edge detection is applied.Canny edge detection has the following stages[18]: (1) Gaussian filter is applied to convolve with the image. It helps in smoothening the image to reduce the effects of obvious noise on the edge detector. The equation for a gaussian filter kernel of size $(2k+1)\times(2k+1)$ is given by:

$$H_{ij} = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{(i-(k+1))^2+(j-(k+1))^2}{2\sigma^2}\right); 1 \le i,j \le (2k+1) \qquad (1)$$

(2) the intensity gradients of the image is obtained using:

$$Edge\_Gradient\ (G) = \sqrt{G_x^2 + G_y^2}$$
$$Angle\ (\theta) = \tan^{-1}\left(\frac{G_y}{G_x}\right) \qquad (2)$$

where G_x and G_y are first derivative in the horizontal and in the vertical direction. G is hypotenuseedge gradient. Angle Θ is the edge recognition anglerounded to one of four angles signifying vertical, horizontal and the two diagonals (0°, 45°, 90° and 135°).(3) Non-maxima suppression as an edge thinning technique. (4) It is essential to filter out edge pixels with a weak gradient value and preserve edge pixels with a high gradient value.(5) Connected-constituent-component-stamping or blob analysisis employed by, observing at a weak edge pixel and its 8-connected locality pixels. As long as there is one strong edge pixel that is involved in the blob, that weak edge point can be recognized as one that should be preserved.In fifth phase, apriori based algorithm is applied. Apriori algorithm consumes a bottom up approach, where recurrent subsets are drawn-out one item at an interval treated as candidate generation, and clusters of candidates are tested against the data. The algorithm concludes when no further successful extensions are found. In this experiment, the enhanced and edge detected image is then segmented as pixel based image segmentation. This generated pixel matrix are then applied to apriori algorithm. Here registered frequent subset value are compared with threshold, candidate generation and clusters of candidates are generated as the region developed. Once the value varies at each pixel subset level algorithm terminates by highlighting region of interest with respect to edges and curved nature of the retina. In final phase, confirmation of whether the disease is present or not is obtained.

The pseudocode for the algorithm is shown for a transaction archive T, and an upkeep threshold of ϵ. Here T is a multiset and Ck is the candidate set. At each stage, it produces the candidate sets from the large itemsets of the preceding level, observing the descendent closure lemma. count[c] approaches a field of the data structure that signifies candidate set c, which is primarily assumed to be zero.The segmented image is stored in matrix form as a separate text file. The algorithm accesses each itemset from the matrix and compares it with the threshold and saves in new data-structure. Once the data-structure is generated the affected portion is known as, its value is different from other non-affected region.By use of apriori algorithm, provided all input datasets and were able to easily segregate between non-affected and affected by achieving 92% performance.

$$
\begin{array}{l}
\text{Apriori}(T,\epsilon)\\
\quad L_1 \leftarrow \{\text{large } 1-\text{itemsets}\}\\
\quad k \leftarrow 2\\
\quad \textbf{while } L_{k-1} \neq \emptyset\\
\qquad C_k \leftarrow \{a \cup \{b\} \mid a \in L_{k-1} \wedge b \notin a\} - \{c \mid \{s \mid s \subseteq c \wedge |s| = k-1\} \nsubseteq L_{k-1}\}\\
\qquad \textbf{for } \text{transactions } t \in T\\
\qquad\quad C_t \leftarrow \{c \mid c \in C_k \wedge c \subseteq t\}\\
\qquad\quad \textbf{for } \text{candidates } c \in C_t\\
\qquad\qquad count[c] \leftarrow count[c] + 1\\
\qquad L_k \leftarrow \{c \mid c \in C_k \wedge\ count[c] \geq \epsilon\}\\
\qquad k \leftarrow k+1\\
\quad \textbf{return } \bigcup_k L_k
\end{array}
$$

IV. RESULTS

A graphical user interface is designed and implemented using MATLAB for the smooth handling of experiments and ease of use. The application is examined with a total of 78 fundus eye images, in which 28 are retinoblastoma-affected eye, and rest are normal healthy eye images. It achieved a good performance and 92% of accuracy. Fig. 5 shows the output after applying preprocessing. The channeling of images helps in correcting and remapping of RGB components of images.

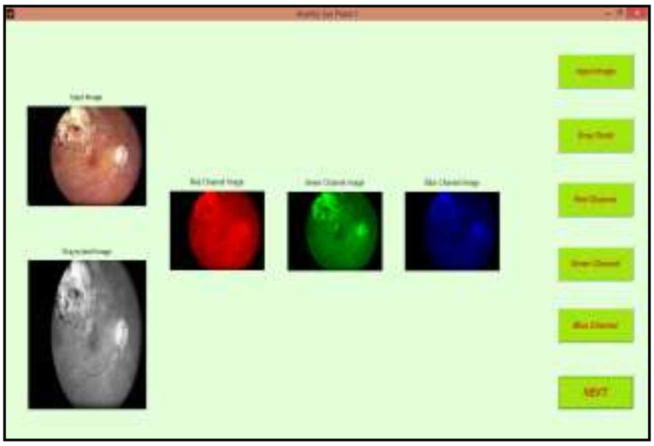

Figure 5. Gray scale, red, green and blue channel images during preprocessing

Fig. 6 depicts, the final output highlighting the region of interest. Fig. 7shows intensity differentiation between normal healthy eye and retinoblastoma-affected eye. Fig. 8 shows result of the application by comparing the input image with reference image.

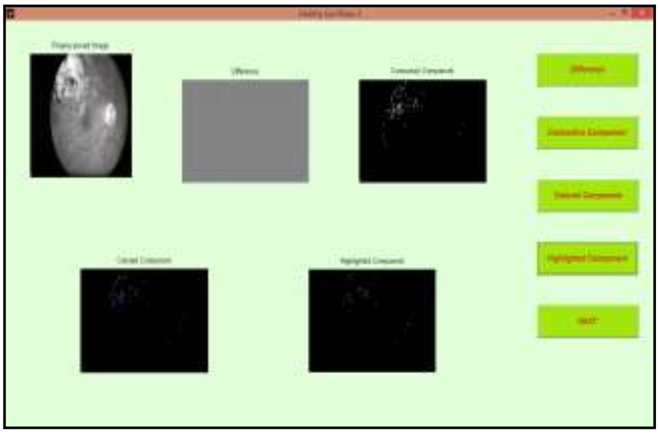

Figure 6. Output showing affected region

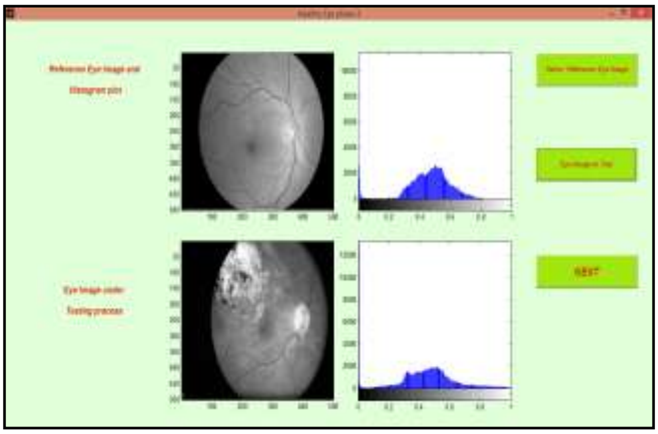

Figure 7. Graph for normal as well as diseased eye

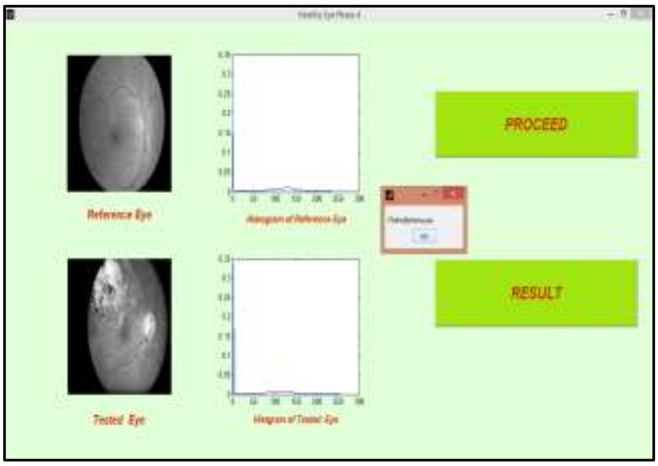

Figure 8. Final output shows in comparison with normal and affected eye

The application is examined with a total of 78 fundus eye images, in which 28 are retinoblastoma-affected eye, and rest are normal healthy eye images.

Acknowledgment

The authors gratefully acknowledge Dr. Balakrishna B.N., M.B.B.S., D.D.M.S., Consultant Surgeon, KMC Hospital, Manipal for his continuing guidance in understanding the disease, suggestions during implementation and validation of the application.

V. Conclusion

This experiment, the detection of retinoblastoma in human eye is carried out using the dataset provided by ophthalmologist.Each step in implementation level is verified and validated by the ophthalmologists. Retinoblastoma continues to be a challenge both diagnostically and therapeutically. It is important to first clearly establish the correct diagnosis before embarking on therapy. Numerous factors enter into management assessments such as patient age, tumor laterality, size, location, and extent, and anticipated visual prognosis. It is quite evident from the end results that this proposed method, based on apriori algorithm is an efficient and accurate method to identify the tumor in retina. This experiment achieved 92% accuracy. Due to the rarity of the disease, people are generally not aware of the possibility of eye cancer. Awareness of the possibility of retinoblastoma and adequate screening is necessary for a better health outcome. With respect to future enhancement, techniques like power spectrum, perimeter area relationship and walking method can be adopted for obtaining better accuracy. Deep learning algorithms can also be utilized for the larger datasets.

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