Automated Vision Defect Detection Supported Deep Convolutional Neural Networks

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Abstract: They should more truly detect abnormalities in the refractive error, used to prevent the children of amblyopia, which can lead to permanent visual impairment, but at first it was detected. A variety of tools have been adopted to protect the area of amblyopia more easily. Amblyopia is a lifetime serious eye disease. Amblyopia contributes to forecasting and treatment and rapid public treatment. They are also useful for completely automatic detection of amblyopia deep neural networks. A tele amblyopia dataset is used for detection. Then proposed deep convolutional neural networks are used for automated amblyopia detection on tele amblyopia dataset. The proposed algorithm comprises of 2 phases. In the first phase, the Enhanced Firefly Algorithm (EFA) is used to segment the eye region. In second phase, a DCNN is designed and trained to classify the segmented eye areas as amblyopia or normal. The test comes about appear that the proposed strategy can work well with the programmed discovery of amblyopia.

Keywords: DCNN, Amblyopia, Neural Networks, EFA, Eye

1. Introduction

The most common cause of permanent visual impairment among children is Amblyopia, with a global prevalence estimated at between 1.6% and 5% [1],[2]. Refractive error is a major cause of childhood amblyopia[3]. Easy detection of childhood refractive errors plays a major role in a visual prognosis [4][5], thus recommending early screening of children and companies by the American Academy of Pediatric Amblyopia and Ophthalmology (AAPOS) and by the European Association of Strabismology [6],[7].

Self-refractors were previously developed for quicker and easier children's refraction. Self-fraction, however, presents several problems, including maintaining the appropriate test position and keeping the visual attachment to the target sufficiently long[8],[9],[10]. The presence of myopia, farsightedness, astigmatism, and anisometropy can be confirmed by photo re-fractional data, by evaluating the type of reflection and position of eccentric imagery crescent in the pupil after projection of the light source on the retina [11],[12].

As far as we know, this is the first research to automate the detection of tele medicinal amblyopia. The main reason is that no published tele amblyopia data sets are available [13]. It is not a trivial task to create a tele amblyopia dataset, as cooperation between ophthalmologists and patients is needed. Furthermore,
the pictures within the tele amblyopia datasets have distinctive sizes, resolutions and foundations, and a few pictures contain as it were a parcel of human faces. These variables make it troublesome to identify amblyopia with telemedicine [14].

Deep convolutional neural networks (DCNN) are able to be used for different applications such as image analysis and interpretation. DCNN has been utilized for vision issues such as farther detecting and therapeutic issues.

The rest of the article is organized in like manner. Area 2 clarifies the writing overview. The points of interest of the proposed strategy for programmed discovery of amblyopia are given in Area 3. In Segment 4, the telemetry based information set and estimation measures are depicted. The test comes about for the proposed strategy is displayed in area 5. The conclusions of this paper are displayed in Segment 6.

2. Literature Survey
In [15] established a revolutionary eye patch neural network. The data loss function and batch normalization layer are used to detect eye segments to diagnose micro aneurysm symptoms.

Existing method established a deep multi-scale sequence neuronal precipitation network for fovea and optic disc extraction. Extracting information from colour background images is seen as a problem of regression. The matrix is then trained and tested on certain amounts of data to detect fovea and optical disc centre after several iterations, without human intervention. Finally, without human intervention, it performed the required extraction task. Existing technique developed a deep neural network that segments the area of the iris from the lower iris images. Initially, the network is provided with a set of high-resolution images for training purposes, which accurately estimates the iris region for segmentation. In the visible and nearby infra-red areas training is carried out to improve the testing process. Conventional methodology have developed a two-level network of waterfalls in order to detect eye landmarks. This method initially estimates an eye condition and then enters the position of the eye, i.e. areas of the eye that are smaller with forecasted eye-points.

3. Methodology
A profound convolutional neural organize to naturally identify amblyopia is proposed in this ponder. The algorithm proposed consists of two steps. First, the segmentation of the area of the eye takes place with EFA. In the second step, the segmented eye regions classified as amblyopia or normal.

3.1 Eye Region Segmentation:
The detection of amblyopia depends mainly on human faces' eye regions. EFA is currently applied to the eye regions for segmentation. EFA is an efficient method for locate disease region. Firefly Algorithm (FA) may be a meta heuristic calculation that mirrors the irregular conduct of tropical summer skies. The firefighting properties were idealized in the firefly algorithm and the following three optimized rules were applied: (1) fireflies are unisex and (2) Engaging quality is specifically corresponding to brightness.

Within the case of two flashing fireflies, they move less strikingly towards the brighter ones. The allure is relative to the brightness and both diminish with increasing separate. In the event that there's no more light than a certain firefly, it'll haphazardly move into the look space. The brightness or light concentrated of a firefly is influenced or decided by the scene of the target component. Within the firefly calculation, the variety of light concentrated and the engaging quality of the definition are two critical issues. For straightforwardness, assume a firefly's engaging quality is decided by its brightness or the escalated of the light, which in turn is related with the objective work.

In arrange to progress the execution of the fundamental firefly algorithm and look worldwide optimum accurately, mutation and crossover operations are incorporated into the firefly algorithm in this section which is inspired from the differential evolution algorithm. The mutation equation is described as (1)
\[ x_{j,k} = x_{\text{best},k} + F (x_{y_1,k} - x_{y_j,k}) \quad (1) \]

where \( i, y, y_1, y_2 \) are the individual population index and are randomly selected to be distinct, \( k \) is the iteration or time, and \( F \) is the scale factor of the mutation, which may be a positive genuine number regularly less than 1.

The point of the hybrid operation is to upgrade the potential differing qualities of the populace. The crossover equation is shown as following equation (2):

\[ x_{j,k} = \begin{cases} x_{y,n} & \text{rand}_{i,n} \leq Cr, \\ x_{y,n} & \text{rand}_{i,n} > Cr \end{cases} \quad (2) \]

where \( Cr \) is crossover probability, \( \text{rand}_{i,n} \) is a random number between \([0,1]\).

In the firefly algorithm, \( \gamma \) is a significant parameter for deciding the meeting rate of how the FA algorithm behaves. To improve the convergence speed of the firefly algorithm, a new method of updating the parameter \( \gamma \) with iteration, the expression can be defined as the following equation (3):

\[ \gamma(t) = t^{(1-0.001)} \quad (3) \]

where, \( t \) represents iteration, \( \text{Max iteration} \) is the maximum of iteration, 1 and 0.001 is maximum and minimum value of \( \gamma \) respectively.

The pseudo codes of IFA calculation is,

Compute introductory populace of fireflies \( x_i (i=1,2,\ldots,n) \)
li at \( x_i \) is decided by \( f(x_i) \)
Find light assimilation coefficient \( \gamma \) by condition (3)
Assume Beginning era, \( k=0 \)
while (\( k < \text{Max Generations} \))
generation number overhauled by \( k=k+1 \)
for \( i=1 \) to \( n \)
  for \( j=1 \) to \( i \)
    compute change through condition (1)
    crossover operation is performed by means of condition (2)
    if \( (I_i > I_j) \)
      Attractiveness shifts with separate \( \gamma \) through \( \exp[-\gamma y_2] \)
  end for \( j \)
end for \( i \)
Rank fireflies and discover the most excellent value
end while
The EFA divides into multiple eye regions, edited to 224 × 224 × 3 and fed into the defined CNN. Figure 1 and Figure 2 illustrate several segmented areas with amblyopia and normal label.

Figure 1: A few model occurrences of fragmented eye districts with amblyopia names

Figure 2: A few commendable occurrences of fragmented eye locales with typical names

In this segment, the parameters of FA and EFA algorithm are set as takes after: α = 0.01, β0 = 1. The tests have been performed on Intel(R) Core(TM) i5-6300HQ, 2.30GHz PC with 8GB RAM. For test reason, 3 distinctive test pictures have been utilized. Test pictures and comparing histograms are displayed in Figure 1. Portioned pictures after the multilevel limit are 512 × 512 in measure. Well known picture preparing parameters such as top signal-to-noise proportion (PSNR), basic likeness list (SSIM) and include similitude record (FSIM) have been utilized in this paper. In picture division, the PSNR parameter is utilized to calculate the crest signal-to-noise proportion between the first picture and the sectioned picture as the underneath equation (4),

\[
PSNR(dB) = 10 \log_{10} \frac{255^2}{\text{MSE}}
\]

Where \(MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (I(i,j) - I'(i,j)) \)

\(M, N\) - size of the image, \(I\) - original image and \(I'\) - segmented image.

The SSIM index can be defined as the given equation (5),

\[
SSIM = \sum_{c} \text{SSIM}(x^{c}, y^{c})
\]

The FSIM index can be formulated as following equation (6),

\[
FSIM = \sum_{c} \text{FSIM}(x^{c}, y^{c})
\]

where, \(x^{c}\) and \(y^{c}\) is \(c\)th channel of the first picture and multilevel fragmented picture separately.

4. Result and Discussions

In this section, the experimental results obtained EFA images are shown. Table 1 gives the PSNR, SSIM and FSIM values based on FA and EFA algorithms obtained at various level \(m = 4, 5, 6\). Table 2 too appears the PSNR, SSIM, and FSIM values between the first picture and its sectioned pictures for each layer and test picture. Clearly, from the test comes about it can be seen that the EFA calculation has way better execution than the FA calculation for the multilevel picture limit division issue.
Table 1: Comparison of PSNR, SSIM and obtained by FA and proposed EFA algorithms

| Image | M | PSNR FA | SSIM FA | FSIM FA | PSNR EFA | SSIM EFA | FSIM EFA |
|-------|---|---------|---------|--------|----------|----------|----------|
|       | 4 | 18.71840 | 0.85501 | 0.82426 | 18.71810 | 0.85521 | 0.82486 |
|       | 5 | 18.73967 | 0.88801 | 0.87123 | 18.73938 | 0.88871 | 0.87172 |
|       | 6 | 18.75178 | 0.91868 | 0.89352 | 18.75133 | 0.91970 | 0.88287 |
|       | 4 | 17.20276 | 0.88483 | 0.87920 | 17.20241 | 0.88405 | 0.85435 |
|       | 5 | 17.21074 | 0.91781 | 0.87835 | 17.21026 | 0.91675 | 0.85375 |
|       | 6 | 17.21938 | 0.93600 | 0.88410 | 17.21870 | 0.93453 | 0.88528 |

4.1 Deep Convolutional Neural Network (DCNN)

After dividing the eye regions, a deep CNN is formed to divide the eye regions. DCNN consists of several rectangular layers of neurons. The neuron cell spatial arrangement is the fundamental feature of DCNN, which can be used for different applications. Furthermore, other key features of DCNN are sparse connectivity, parameter sharing, and pooling. Shortcut connections allow networks to skip layers, and speed training is also possible. The general structure of the profound learning method we propose in this work is shown in Figure 3.

![Figure 3: Structure of the basic block and the shortcut connection](image)

Sparse Connectivity: This shows that every neuron in DCNN is connected only to a small area of neurons in the anterior or posterior layers.

Parameter Sharing: This means that the same layer of nerve cells has the same parameters. One set of parameters should be calculated instead of calculating a separate set of parameters for each new location.

Pooling: Aggregations are performed from the output of neurons. The maximum grouping function is the most common grouping function that groups nerve cells and generates the maximum value in a rectangular area.

4.1.1 Datasets:
The tele amblyopia dataset contains 5,685 pictures. Each picture contains as it were a human confront. 5,310 pictures contain total human faces, whereas 375 pictures contain parts of human faces. The tele
amblyopia dataset is partitioned into a preparing dataset containing 3409 pictures and a test dataset containing 2276 pictures. The preparing dataset comprises of 701 amblyopia pictures and 2708 ordinary pictures, whereas the test dataset comprises of 470 amblyopia pictures and 1806 ordinary pictures at that point picture resolutions are 1033×900 to 78×150.

4.1.2 Evaluation Metrics:
The Affectability, Specificity and Precision assessment measurements are utilized in this try to assess the execution of the proposed strategy the following equation (7):

\[
\begin{align*}
\text{Sensitivity} &= \frac{TP}{TP+FN} \\
\text{Specificity} &= \frac{TN}{TN+FP} \\
\text{Accuracy} &= \frac{TP+TN}{TP+TN+FP+FN}
\end{align*}
\]

Here TP (genuine positive), TN (genuine negative), FP (untrue positive) and FN (untrue negative) are the numbers of accurately distinguished amblyopia pictures and recognized ordinary pictures.

**Table 2:** Comparison of Accuracy, Sensitivity and Specificity of the proposed DCNN with conventional methods

| Classifier/Metrics | Specificity | Sensitivity | Accuracy |
|--------------------|-------------|-------------|----------|
| SVM                | 91.25       | 92.18       | 91.07    |
| Adaboost           | 94.56       | 94.68       | 94.73    |
| RF                 | 95.15       | 95.14       | 95.64    |
| DCNN               | 98.29       | 97.92       | 98.20    |

**Figure 4:** Performance metrics with various classifiers

The results of accuracy, sensitivity, and specificity between the DCNNs offered for the SVM, Adaboost and Random Forest classifications are shown in Figure 4 and Table 2. The result shows that the high accuracy proposed for the DCNN is 98.20, the sensitivity is 97.92 and the specificity are 98.29, compared to the Adaboost, Random Forest classification.
5. Conclusion
To automatically detect amblyopia from telemedicine, a dataset for telemedicine amblyopia is used in this work, in which picture information is collected and labeled by masters. The proposed algorithm first uses EFA to segment the eye region and then classify the regions of the fragmented eye as amblyopia or as a profound convolutional neural organize. Execution is decided by reference to the ideal limit values of PSNR, SSIM and FSIM. The numerical results demonstrate better performance of the EFA algorithm than the FA algorithm. Deep convolutional neural networks (DCNN) are subsequently suggested to automatically detect amblyopia. In the DCNN network, it can be observed that high accuracy of 98.20, sensitivity is 97.92 and specificity is 98.29 could be achieved in the algorithm proposed indicating that good detection performance in amblyopia identification of amblyopia images and normal image. The results of the detection in the established telemedicine data set show that the algorithm proposed works well with the automated detection of telemedicine amblyopia.

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