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AUTO HYPERTENSION DETECTION AND HEALTH CLASSIFICATION USING BIO-INSPIRED MACHINE LEARNING ALGORITHMS

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ABSTRACT

Hypertension, or increased blood pressure (BP), may injure blood veins in the retina of an eye, resulting in a condition known as hypertensive retinopathy (HR). Hypertension causes blood to enlarge as well as the retina's function to deteriorate. The most common way to identify HR in a person's blood is by a medical assessment using an ophthalmoscope that is still done manually by an ophthalmologist. It takes a very some duration for a physician to detect a particular member on the eye fundus picture in a very manual method. To solve this challenge, a mechanism for automatically identifying the picture of the retinal fundus is required. The backpropagation bp neural network was utilized in this study to identify the retinal fundus. Pre-processing green channel, contrasting limit adaptive entropy equalization, morphology proximity, background subtraction, threshold, or linked components analysis, and extracted features utilizing zoned were done before recognition. The findings demonstrate that perhaps the suggested approach can immediately recognize the retinal fundus 95% of such time with a maximal period of 1500.

Keywords: Machine Learning, Hypertension detection, Classification, Blood pressure, Green channel; Healthcare

INTRODUCTION

Hypertension seems to be a condition that manifests itself in many ways across the human body. That occurs when blood pressure (BP) rises over a safe level, posing a risk of retinal injury. Hypertensive retinopathy is a condition in which the retina is damaged as a result of high blood pressure **[1]**. HR is a hard retinal injury caused by high BP accumulating in the eye for many days, for the individuals those are preferred to use BP medications **[2]**. According to the findings of the 2013 General Healthcare Survey, the number of people with hypertension decreased from 31.7 % to 25.8 % over six years. According to existing data, persons over the age of 18 accounts for 25.8% of total victims, and males get a greater risk of hypertension throughout their successful years. Nevertheless, this does not apply to persons in their early 50s or beyond, because women in this age group have a greater risk of contracting the condition.

Hypertension induces hypertensive retinopathy (HR), which damages the retina. When a blood vessel swells as a result of hypertension, the retina's function suffers **[3]**. Ophthalmologists still use fundoscopy to diagnose hypertensive retinopathy conditions in the majority of cases. As a result, a technique is required to assist the ophthalmologist in automatically detecting hypertensive retinopathy to get better inspection outcomes than manual assessment.

Literature Review

Quinn and Krishnan's goal is to separate blood arteries in diabetics & hypertensive retinopathy victims. Use the greens channels in the preparation step to display the veins stronger than the backdrop picture. The equalization histogram then enhances picture contrasts by altering the picture's luminance. Curvelet transforms are used to show a picture with boundaries. Using MSE Morphology, a customized Top-Hat transformation is used to detect the edges. Utilizing morphological openness by rebuilding to remove the incorrect margins which are not components of the blood vessels **[4]**. Then CCA and Length Filtering is used to correctly remove the incorrect border remains. Blood vessel identification may be completed in much less than a minute **[5]**.

Agurtoet colleagues acquired characteristics of hyperten retinopathy (HR) like Ag/Cu wire, and vein anomalies by analyzing a digitally colored fundus picture. To identify HR, such features are utilized as parameters for regression model classifiers to classify them. That study's findings have a precision rating of 85% **[6]**. Researchers used contrast limit adapt histogram equalization (CAHE) on greens channels to identify excess fluid on colored fundus pictures in diabetic retinopathy, the initial onset of enhancing quality images. Utilizing median filtering and thresholding, red bands can also be used to identify and stop optic discs within images. Applying K-means grouping in the segmentation step **[7]**. GLCM and Lacunarity are used in the feature extraction step. The accuracy of the classification to use the Naive Bayes technique was 92.13 %.

Further, it was classified diabetes using fundus imaging techniques. Utilize adaptable histogram equalization (AHE) to remove unwanted portions of the backgrounds during the preliminary step. Separation of blood arteries is done using 2-D Gabor Wavelets. Grey-level co-occurrence is used in the feature extraction phase. SVM is often used to distinguish between a healthy retina and diabetes retinopathy. In **[8]**, a CT Scan picture was used to diagnose lung cancer. The RGB image is converted into a monochromatic and black picture during the preliminary step, and afterward, the picture enhancement procedure is completed. For picture element retrieval, a genetics method is applied. Depending on tumor volume and cancer phase, a backpropagation neural network is utilized to categorize pictures of lung cancer as positive or negative **[9]**.

The diagnosis of hypertensive retinopathy illness using a retinal fundus picture is known as Nurrahmadayeni. The procedure of picture extracting features utilizing two approaches, fractal dimension and unchanging periods **[10]**, is conducted before recognition. The Box Counts method was used to calculate the fractal dimension. Next, for regular retinal categorization or hypertensive retinopathy, apply the Probabilistic Neural Network technique. That study yielded a perfect recognition rate of 100 % accuracy **[11-12]**.

Sandri is a method for detecting retinoblastoma using a retinal fundus picture. Picture analysis, visual quality enhancement, and picture feature retrieval utilizing grey level co-occurrence are the phases that are completed **[13]**. Whether regular retinal categorization or retinoblastoma, the backward transmission NN approach was utilized. The reliability of the detection accuracy in this study was 90% **[14-15]**.

Research methods

Throughout this study, the diagnosis of hypertensive retinopathy is accomplished by a series of stages that begins with retinal fundus pictures that include both regular and hypertensive retinopathy data captured using Analysis of Retina. That information was utilized for both experimentation and testing, with a greens stream procedure applied to a retinal fundus picture to better display the veins and retinal components **[16]**. CAHE is often used to improve contrast and reduce noise, allowing blood vessels & retinal components to be viewed more distinctly. Optical disc and backdrop are eliminated via physical close. Separation also transforms a picture into a digital picture by utilizing the threshold process. Whenever the thresholding method leaves items smaller than 70 pixels, linked component analysis is used to remove these. During retinal fundus recognition, an extracting features approach based on zones and a backpropagation neural network is used. The next chapters will go through each stage in depth. The structure of **Figure 1** depicts the technique used in this study.

Green Channel

The greens stream is used in the initial phases because it has the greatest light reflections and can generate more detailed images of blood vessels & retinal architecture than the red and blue streams. The greens channel is made up of RGB color. The following expression may be used to compute it:

$$(x, y) = 0.R + 1.G + 0.B = G \quad (1)$$

The Contrast Limit Adapt Histogram Equalization approach is used in the following stage of picture contrast augmentation and is a more advanced variant of the earlier Adaptive Histogram Equalization technique. That is used to improve contrast so that veins and retinal structure may be seen properly, as well as to reduce noise and provide a histogram border value.

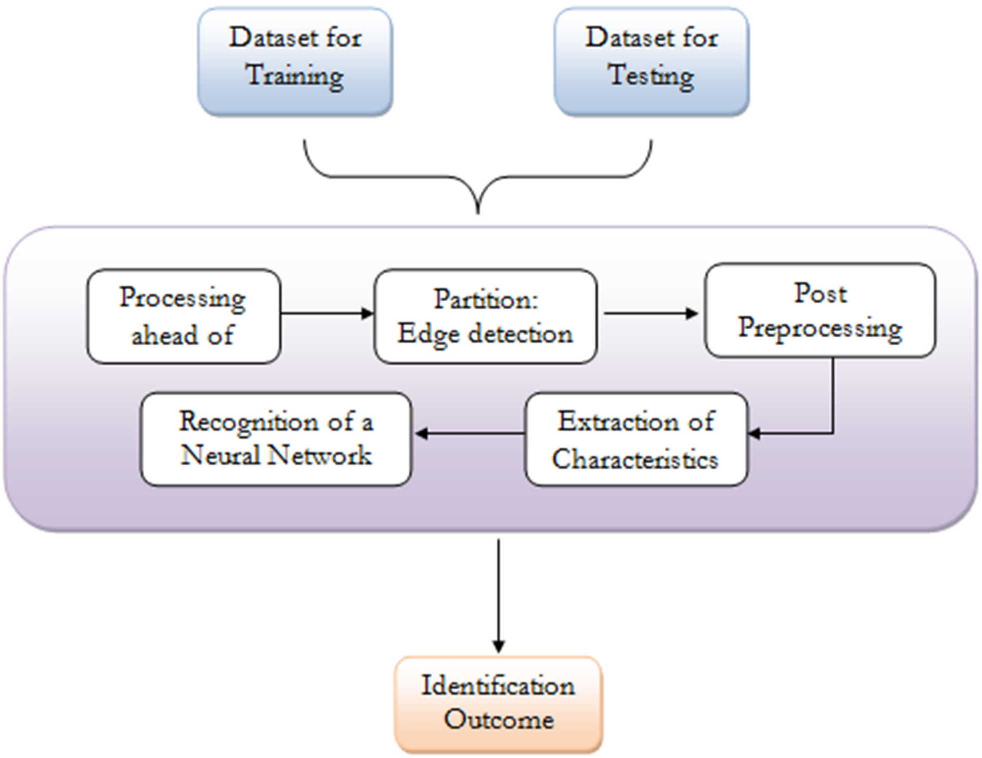

Figure 1: Architecture Diagram

Because an item doesn't contain the features to also be retrieved, the following phase splits the backdrop & optical disc utilizing morphology near. Narrowing & corrosion are morphologically related. This phase of dilatation is followed by the corrosion process.

The following formulas are used to estimate the dilation and erosion

equations 2 and 3:

(X,Y) = XØY = {:Yx ∩ X not equal θ } (2)

(X,Y) = XØY = {:Yx ∩X} (3)

Thresholding. Now next step is normalization, which produces a digital picture with values of 0 and 1. The following expression could be determined by calculating:

(A, B) {1ifA, B) > S O id f(A,B) ≤ S (4)

Post Processing

The next step is to do a linked method to eliminate items that aren't veins. Entities with a size smaller than 70 pixels and that is not deemed blood arteries were removed. The concept of integration may be used to identify areas or entities in digital pictures. That approach makes use of the picture's connection pixels concept. Whenever the pixel inside the zone satisfies the pixels criteria, they were considered linked. That pixels rule takes use of the pixel dimensions' characteristics, as well as the previous pixels' adjacent connections. There are 2 kinds of communication: 4-connected neighbors and 8 connected neighbors. **Table 1** shows four points of connection.

Table 1: Connectivity for a group of four neighbors

S(a-1, b)	**S(a-1, b)** **S (a, b)** **S (a, b+1)**	**S (a, b+1)**

Table 2: Connectivity for a group of eight neighbors

S(a-1, b-1) **S (a-1, b)** **S(a+1, b+1)**	**S (a, b-1)** **S(a, b)** **S (a, b+1)**	**S (a+1, b-1)** **S (a+1, b)** **S(a+1, b+1)**

Feature Extraction

Zoning. Scheduling is a way of dividing a region into MxN squares. The image is split into regions, with each region generating attributes by collecting the largest number of white pixels. At this point, the 700 × 605-pixel picture would be split into 10 columns and 10 rows, yielding 100 zones ensuring 100 characteristics. The image resolution utilized for this spacing approach for each region is 520 pixels.

Within characteristics separator on a retinal image, the area method has been used to:

- Reduce X1 from X100 to find the proportion of white dots for each region.
- Choose the region with its most grayscale.
- Using Formula, estimate the characteristic quantity of each region from X1 to X100.

$Feature\ Value\ Xn = Xn\ /\ X\ highest$ range $1 \leq x \leq 100$

Region can be calculated as:

- total Number of dots for each region: Z1 = 80, Z25 = 150, Z50 = 250, Z90 = 190, and etc.,
- The region with the largest proportion of white pixels is Z40 = 200.
- Every region's valuable features encompass:

$X1 = 80/250 = 0.32$

$X25 = 150/250=0.6$

$X50 = 250/250= 1$

$X90 = 190/250=0.76$

Round the characteristics for all zone:

$Xn < 0.5, Xn = 0$

$Xn \geq 0.5, Xn = 1$

This is done such that the generated feature number is indeed a numeric value, which can be used as input information in the classification phase of the next batch. As a result of the region computation, the characteristic score of $X1 = 0$, $X25 = 1$, $Z\ 50 = 1$, $Z90 = 1$.

According to **Figure 2**, the features separation step of the zoning computation would generate 100 characteristics which will be used as input values in the classification stage.

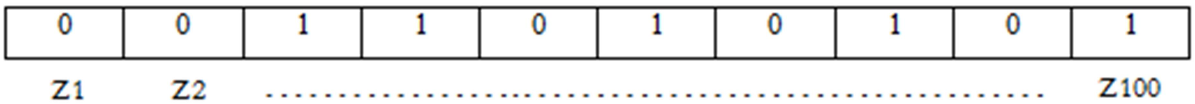

Figure 2: Using zoning to extract value from features

Neural Network. Following obtaining the feature value from the Zoning information extraction procedure, the picture classification technique utilizing the Backward propagate NN technique follows. Backward propagate NN arhitecture conceptual design, training stage, and back propagation test phase are the phases. The following formula **[14]** can be used to compute it:

1. initialization

(−2,4/Ej, +2,4/Ej)

2. Activation (Feed Forward)

xi (s) = $sigmoid$ [Σ aj (s). xjk (s) mj =1]

b(s) = $sigmoid$ [Σ aki (s).aki (s) ni =1]

3. Training Weights

δi (s) = bi (s) − aedi (s)

Δaki (s) = α. bji(p). δi (s) − μ. Δaki (s − 1)

xki (s + 1) = aki (s) − Δzki (s)

δ(s) = [Σ δi (s).xki (s) ni=1] . bk (s). (1 − bi (s))

Δxj(s) = α. aj (s). δk (s) − μ. Δxj(s − 1)

xj(s + 1) = xjk (s) − Δxki(s)

CONCLUSIONS

The following are the results that can be drawn from evaluating the hypertensive retinopathy illness diagnosis system utilizing a retinal fundus picture and a Backpropagation Neural Network:

- Backpropagation neural network as a classification method according to the stated objective may be used to identify retina fundus images with a 95% accuracy.
- The reliability of the outcome is affected by the attribute values chosen for the backpropagation neural network. At the greatest value of epoch 1500, parameters assessment at backpropagation neural network parameter offers the reliability of 95%.

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