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Machine Vision Based Identification of Eye Cataract Stages Using Texture Features

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Abstract: Blindness has many reasons, cataract is one of them. A cataract is formed due to opacity or cloudiness or dullness of the human eye lens. Human vision is decreased gradually as the impurities gathered in front of the human eye lens. Traditional eye cataract examination requires expensive instruments. A novel framework of texture features based analysis designed to correctly identify the presence of cataract in the human eye. The eye image dataset of two categories namely normal and cataract have been taken from a high-resolution digital camera. It has been observed that each digital image of a dataset contains 220 texture features, although 30 enhanced features for each image has been acquired by joining three feature selection approaches, namely Probability of error (POE) with Average Correlation Coefficient (ACC), Fisher (F) and Mutual Information (MI). These 30 enhanced features dataset has been deployed using Artificial Neural Networks. ANN (n-class) deployed and acquired an accuracy of 99.38%.
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1. Introduction

The conventional methodologies are present to identify the presence of eye cataract in humans [1]. The real-time datasets are important for sustainable development, assessment and resource management [2]. Cataract has many reasons that are age-related, accidental, ultraviolet rays, etc. When a cataract is produced in the human eye then incident light is not passed through the human eye lens. Many conventional methods for eye cataract detection have been used by ophthalmologists which are slit-lamp identification, light focus method, iris image projection method, etc. [3]. In recent years, artificial intelligence has been used in different domains like medical, environment, soil and natural science, etc. very hot research area for scientist [4]. Many researchers employed this technology in these areas and acquired very healthy results [5]. Retro-illumination lens images used by [6] and acquired 84.8% accuracy. Fundus images are used by many researchers for analysis of cataract. Fundus image-based cataract classification and grading calculated by using linear discrimination analysis (LDA) with AdaBoost algorithm as a classifier and acquired accuracy between 81.52% and 95.22% [7] [8] [9]. Microscopic images of cataract lens with different hardness degree have been inspected with K-nearest neighbor classifier and acquired accuracy of 92.5% [10]. Fundus images have been used by [11] and acquired 92% accuracy. [12] use slit-lamp images, applied statistical texture analysis and acquired 97.5% accuracy.

This research shows novelty about the methodology that is adopted. The rare concept of this experimentation is that all images were taken digitally without using any ophthalmological tool.

1. Study Area

All the experimentation has been performed at image processing lab, The Islamia University of Bahawalpur, Punjab province (Pakistan), Department of Computer Science & IT, image processing lab, located at 29°23′44″ N and 71°41′1″E. This research describes the identification of eye cataract using digital photographic data.

2. Data set

For this study, digital images of cataract have been acquired from the department of ophthalmology, Bahawal Victoria Hospital (BVH). A SAMSUNG digital camera having 8-megapixel, 3264×2448 of image resolution has been used of the image dataset. Digital images [13] of 32 patients have been acquired in the presence of experienced ophthalmologists.

3. Methodology

The main objective of this research is to identify the presence of cataract through image processing. An effective framework is designed to identify cataract accurately.

3.1. Proposed Methodology

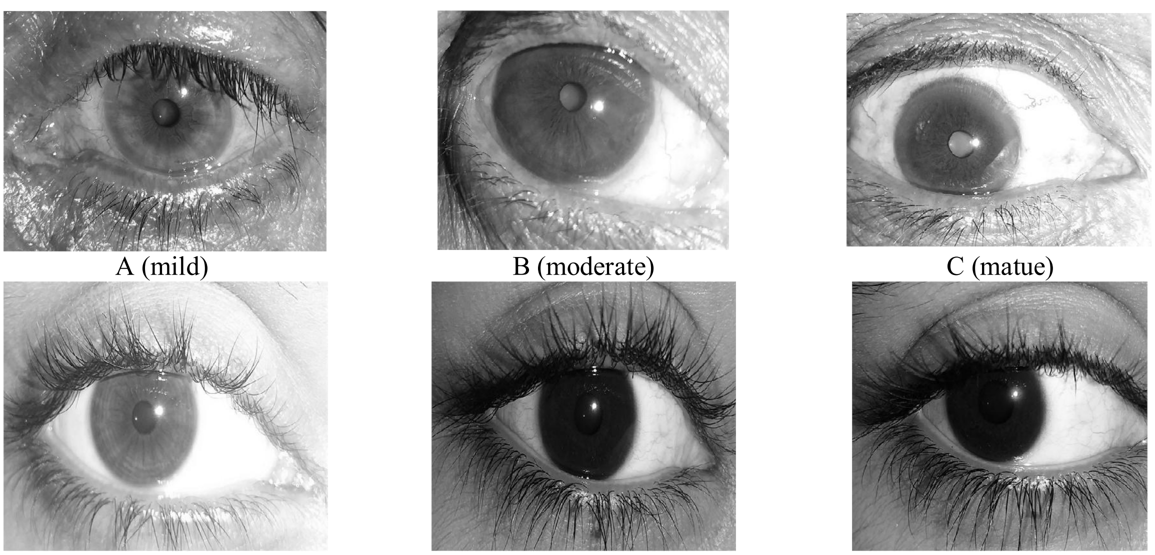
A framework is proposed for subjective cataract identification. To identify cataract image processing steps have been applied namely image preprocessing (image cropping, gray-scale conversion, bitmap conversion), texture feature elicitation, texture feature selection, feature optimization, and analysis have been adopted. The proposed algorithm has been implemented using MaZda 4.6 with b11 [14]. A proposed algorithm for the identification of eye cataract described:

Proposed Algorithm

Start Main
Input →Digital Image dataset
For
{
Step 1 to Step 5
Step 1 → Splitting image dataset → {cataract, normal}
Step 2 → Preprocessing→ image resize, color to grey, jpg to bmp
Step 3 → Statistical texture feature extraction → {Mean, Angular Second Moment, etc.}
Step 4 → Feature Reduction techniques → **(F + PA + MI)**.
Step 5 → The 30 Optimized feature dataset received
End For
}
Step 6 → Computer Vision classifier applied.
Output → Identification of cataract Results
End Main

3.2. Digital Image Data Acquisition

Digital camera with a still stand has been used to get eye images. The distance between eye and camera is 0.5 feet. Thirty two patient data of eyes have been acquired, five images of each patient ($32 \times 5 = 160$), captured with 3264×2448 resolution, 24-bit depth, and 72 dpi horizontal and vertical resolutions in joint photographic expert group (jpeg) format.



A (mild) B (moderate) C (matue)
D (normal) E (normal) F (normal)

Figure 1: Eye Image dataset

Non overlapping region of interest (ROI) i.e., (20×20, 25×25, 50×50, 75×75) created on image size (512×512) [15]. The data collection process is completed under controlled environment and in the presence of experience ophthalmologist.

Segmentation. Image segmentation step is applied to extract the region from where we can get segmented pixel based threshold data [16].

3.3. Proposed Framework

After the collection of the image dataset, the proposed framework is used for further processing and analysis. Before starting the further processing, the extraneous portion from each image is removed. Digital colored images of eyes are transformed in gray level and converted in.bmp (8 bit) format. For this study, the software is used for texture features calculation. Some of these features named as Moment 2, Inertia etc. [17]

$$Moment\ 2 = \sum_x \sum_y (x-y)^2 M_r(x,y) \quad (1)$$

$$Entropy = -\sum_w D_{i-k}(w) \log_{D_{i-k}}(w) \quad (2)$$

Total 220 texture features are computed for each ROI resulting from gray-level co-occurrence matrix (GLCM) in four directions (0°,45°, 90°, 135°) up to 5-pixel distance [18] as shown in figure 2. It means that each ROI has calculating 220 statistical texture features. The total number of accessible image data is 35200 (160×220). The amount of data collected is huge. It is important to reduce features dimensionally to acquire the most discriminate features.

3.4. Feature Selection

In this study, we have used three supervised feature selection techniques such as, Probability of Error with Average Correlation Co-efficient (POE + ACC), Mutual Information (MI) and Fisher Co-efficient (F) [14].

$$Fisher\ coefficient = \frac{L}{M} = \frac{\frac{1}{1-\sum_{a=1}^{A} P_a^2} \sum_{a=1}^{A} \sum_{b=1}^{A} P_a P_b (\mu_a - \mu_b)^2}{\sum_{a=1}^{A} P_a M_a} \quad (3)$$

Above mentioned equation (3) is of fisher coefficient where L denotes between-class scatter, M is the class variance, μ_a mean of class a, P_a probability of class.

$$M^1 = M_g : min_g\left[C_1 POE(M_g) + C_2 ACC(M_g)\right] \quad (4)$$

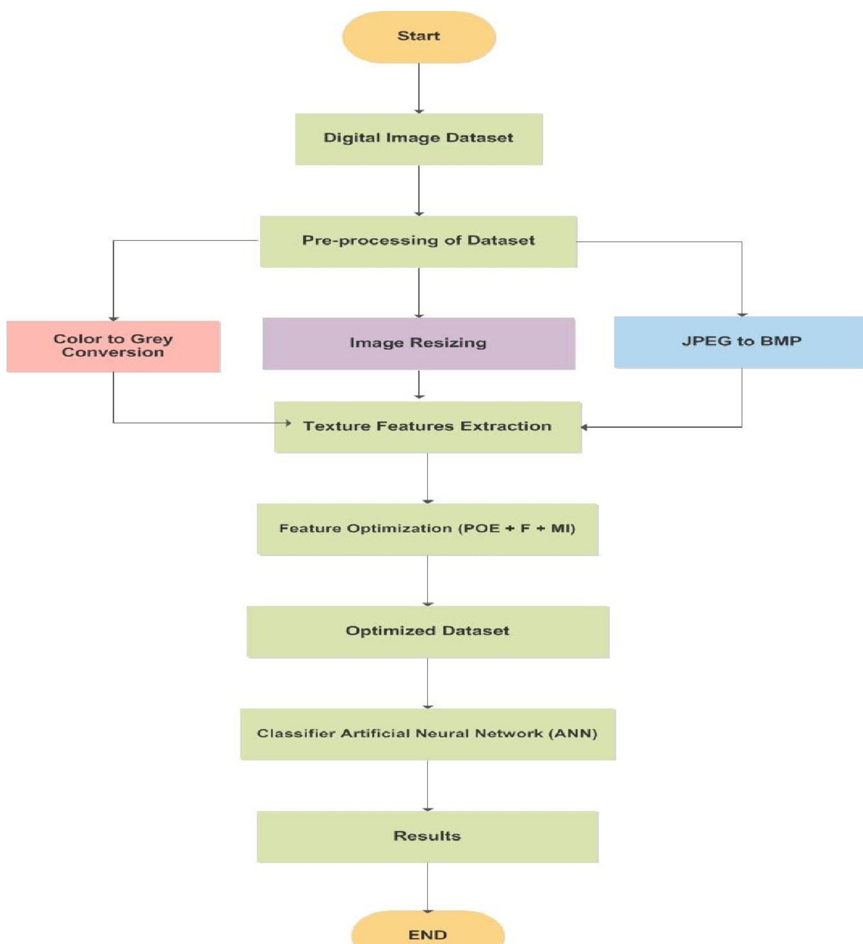


Figure 2: Proposed Identification of Cataract Framework

In equation (4), $POE(M_g)$ is the probability of classification error for feature M_g, two weight values C_1, C_2 are present in above formula.

$$Mutual\ Infromation\ (F_l, D) = \sum_{D=1}^{M_b} \sum_{n=1}^{M_c} P(F_l^D, C_n) \log_2 \left[\frac{P(F_l^D, C_n)}{P(F_l^D) P(C_n)} \right] \quad (5)$$

Equation (3) describes Mutual information, where P means the probability, $\boldsymbol{F_l^D}$ is discrete value of feature $\boldsymbol{F_l}$, $\boldsymbol{D = \{C_1, C_2, \cdots, C_{M_C}\}}$ represents class category, $\boldsymbol{M_b}$ is a constant and equals to $[\mathbf{log_2}(\boldsymbol{N}) + \mathbf{1}]$, where N is the total number of samples of feature $\boldsymbol{F_l}$. Each technique gave 10 most discriminate features. A total of 30 features are selected with these feature selection techniques. These combined features (F + PA + MI) give better accuracy results [15]. The selected texture features are shown in

Table 1:

Table 1: Most discrimination features by applying feature selection technique (MI + F + PA)

MI + F + PA		
1 S (2,0)SumVarnc	11 S (5,-5)Correlat	21 S (1,0)DifVarnc
2 S (1,-1)SumVarnc	12 S (4,4)SumAverg	22 S (1,1)DifVarnc
3 S (5,5)SumOfSqs	13 S (2,-2)DifVarnc	23 S (1,-1)DifVarnc
4 S (1,1)SumVarnc	14 S (0,1)Contrast	24 S (1,1)Contrast
5 S (5,5)SumVarnc	15 S (3,0)Correlat	25 S (1,-1)Contrast
6 S (0,3)SumVarnc	16 S (3,-3)DifVarnc	26 S (0,1)DifVarnc
7 S (4,4)SumOfSqs	17 S (4,0)Correlat	27 S (0,2)DifVarnc
8 S (3,3)SumOfSqs	18 S (3,3)SumAverg	28 S (2,0)DifVarnc
9 S (2,2)SumOfSqs	19 S (1,0)Contrast	29 S (2,0)Contrast
10 S (3,0)SumVarnc	20 S (1,0)InvDfMom	30 S (1,0)DifEntrp

4. Results and Discussion

Four different sized ROIs have been created i.e., (20 × 20, 25 × 25, 50 × 50, 75 × 75) on image size (512 × 512). On these ROIs, optimization techniques like principal component analysis (PCA) [20], raw data analysis (RDA), linear discriminant analysis (LDA) and non-linear discriminating analysis (NDA) to inquire data clustering capabilities. At first step, we have taken ROIs of (20 × 20) and deployed data clustering technologies namely RDA, LDA, PCA, and NDA. It has been observed that NDA gives better clustering results of 91.14% as compared to other clustering technologies. In step2, ROIs of (25× 25) have been taken and the same structure has been employed and it shows better clustering results of 91.99% using NDA as compared to other technologies on ROI (20×20). In step 3, the ROIs of (50×50) have been taken and the same procedures have been applied, it shows better results of 100% using NDA as compared to other clustering technologies. In step 4, ROIs of size (75×75) have been taken and got a clustering accuracy of 98.75% using NDA. NDA framework has been shown in each technique gave 10 most discriminate features. A total of 30 features are selected with these feature selection techniques. These combined features (F + PA

+ MI) give better accuracy results [15]. The selected texture features are shown in Table 2.

Table 2: NDA framework texture dataset

Input Layers = 2	1st layer = 4	2nd layer = 2
Learning rate eta = 0.15	Back propagation iteration = 150000	Optimized repetition limit = 50
Output layers = 2		

The results of data clustering technologies on above mentioned ROIs summarized in Table 3. Data clustering of 2 input eye classes in NDA projection space is shown in Figure 3: **NDA results of data clustering of statistical texture features** show the NDA results of data clustering. A summary graph of all used clustering technologies has been shown in Figure 4.

Table 3: Comparison of Data Clustering techniques on different ROIs

Statistical data analysis on ROIs	RDA	PCA	LDA	NDA
20 × 20	68.72%	69.77%	69.35%	91.14%
25 × 25	67.95%	69.23%	58.33%	91.99%
50 × 50	80.86%	79.63%	73.46%	100%
75 × 75	79.37%	77.50%	75.62%	98.75%
Average accuracy	74.23%	74.03%	69.20%	95.47%

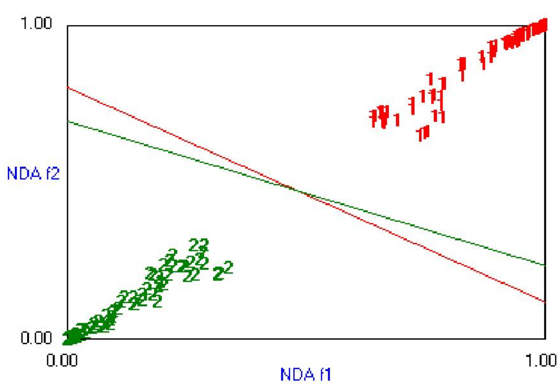


Figure 3: NDA results of data clustering of statistical texture features

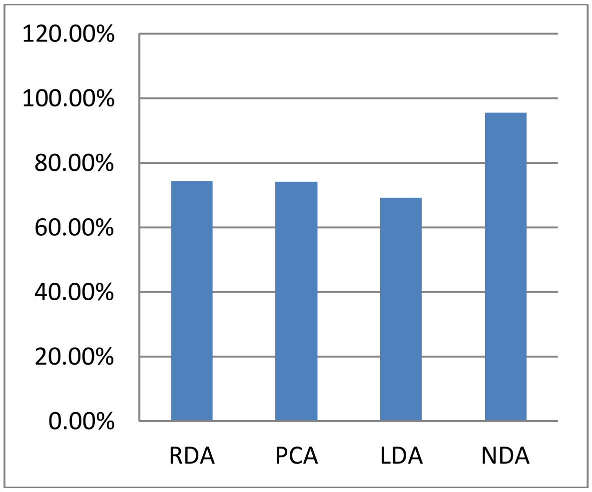


Figure 4: Summary graph of data clustering techniques

After the feature reduction procedure is implemented. An Artificial Neural Network (ANN n-class) **[19]** has been employed on a reduced dataset and acquired 99.38% accuracy. The accuracy table for cataract and non-cataract has been shown in

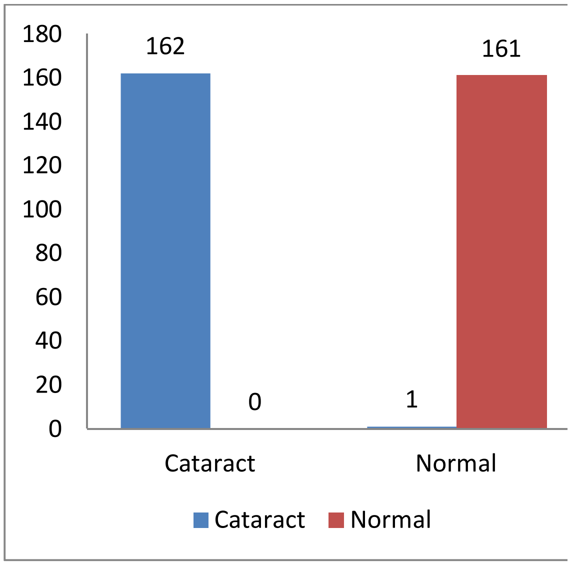


Figure 5: Confusion graph for statistical texture data classification

Table 4 and graphical representation in Figure 5.

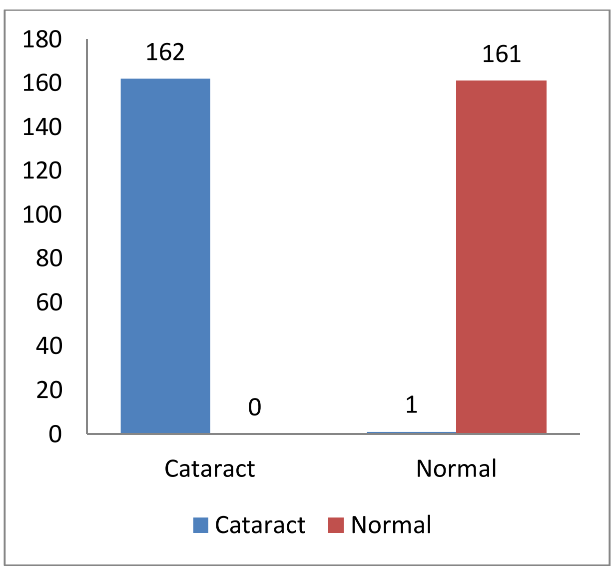


Figure 5: Confusion graph for statistical texture data classification

Table 4: Confusion table for texture data classification

Type	Cataract	Normal	Total
Cataract	162	0	162
Normal	1	161	162

Finally, comparison of cataract identification and proposed approach has been discussed in Table 5.

Table 5: Comparison of different methodologies and proposed methodology

Ref. No.	Feature Extraction	Classifier (s) used	Accuracy (%)
[8]	GLCM 24 features, GGCM 15 features	Back propagation	82%
[9]	Spectrum from 2D, DFT fundus image	PCA, LDA with Adaboost algorithms	Two class 95.22%, Four class 80.52%
[20]	Small, big (ring area), perimeter	SVM (Support vector machine)	88%
[21]	Intensity of lens and sulcus, posterior color, reflex, intensity ratio	SVM	Nuclear cataract 76%, cortical cataract 73%
[22]	Contrast dissimilarity and uniformity using GLCM	KNN method	94.5%
[23]	Convolutional filters, Convolution, Pooling	Deep convolutional Neural Networks (DCNN)	93.52%
Proposed Approach	Digital images, GLCM with NDA	ANN (n-class) classifier	99.38%

5. Conclusion

In this study, two types of digital images of the eye are classified by using quantifiable parameters instead of conventional parameters and acquired accuracy of 99.38% for the statistical texture dataset. Eleven second-order co-occurrence matrix features have been utilized to test the human eye dataset which made this expected schema innovative, more definite and prosperous than other frameworks in which morphological, size, color, geometrical and spectral features have been used. Artificial Neural Network (ANN n-class), is used to classify the different eyes such as cataract and normal. In the future, we may upgrade this research for data fusion using digital image data considering multiple factors such as luminance, sharper images and minimize the other luminance effects.

Authors Contributions

The main concept and experimentation were performed by Muhammad Shehzad and Dr. Salman Qadri made critical revisions and approved the final paper. All co-authors reviewed and approved the final manuscript.

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