Glaucoma Image Classification Using Entropy Feature and Maximum Likelihood Classifier

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Abstract. In general, the nerve that links the eye to the brain is affected because of high eye pressure. The most common kind of glaucoma sometimes has no other symptoms than a gradual loss of vision. In this study, the Glaucoma Image Classification (GIC) is made by using different entropy features and Maximum Likelihood Classifier (MLC). Initially, the input fundus images are decomposed by using rankles transform, then the entropy features like sample entropy, Shannon entropy and approximate entropy are used to extract features. Finally, MLC is applied for classification. The GIC scheme’s function produces the classification accuracy of 96% by using Shannon entropy feature and MLC.

Keywords: Glaucoma, Ranklet transform, Maximum likelihood classifier, Entropy feature.

1. Introduction
Glaucoma is an eye nerve injury condition normally occurs as fluid builds up on your eye front. This extra liquefiwed increase the pressure in the eye as well as affects the optic nerve. The detection of multiclass glaucoma is defined in [1] based on new fractal features. Based on the fractal analysis, glaucoma characteristics are derived by a fractal dimension box counting procedure. For classification, the kernel-based Support Vector Machine (SVM) classifier is used.

A combination of multiple deep characteristics is defined in [2] for the classification of glaucoma. The area of interest is initially derived from the image of the input glaucoma. A convolutional neural network derives the features. The softmax layer and SVM classification are used. The automated evaluation of glaucoma is discussed [3]. Features like the capillary density and retinal nerve fibre layer are being extracted. For classification, the SVM classification with a linear classifier is used.

Median and wiener filters are used to eliminate noise from the input fundus images. The histogram equalization approach is then used as an optimization tool for pre-processing [4]. The removal of the optic disc, binarization and noise and active contour models are applied to excerpt the feature. The classification is rendered through the procedure and SVM classification of neuro-fuzzy adaptive inference system [5]. For glaucoma image classification, spectral and texture characteristics are listed.

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Convolutional image classification approaches based on neural networks can use more image indicators to achieve good efficiency—a new classification of glaucoma by integrating several characteristics derived from various neural Convolutional networks [6]. The function extraction method is initially performed via discrete transform wavelet. The key component analysis technique then selects features or decreases features. Finally, for the classification of glaucoma images, a convolutional model has been applied [7]. A standard dataset is functional to verify the convolutional method’s productive outcomes, and the results are tested in different dimensions.

The function extraction method is initially performed via discrete transform wavelet. The key component analysis technique then selects features or decreases features [8]. A benchmark dataset is applied to verify the convolutional method’s productive results, and the results are tested in different dimensions. Identifying and visualizing some updates in the Visual exterior temperature. For pre-processing, the proposed approach uses a linear transformation [9]. In a classifying the specified visual, thermal image in eye disease from normal, the logistic regression classification based on the features gathered in grey levels co-occurrence matrix.

The pre-processing methods like filters, the extraction of the green channels and visual, active contours, and blood vessels segmentation are proposed. They are proposed to be extracted to remove features [10]. Classification based on the artificial neural fuzzy inferencing and SVM is given for extracted properties.

A GIC using entropy feature and maximum likelihood classifier is presented in this reading. The rest of the strategy is arranged as surveys: Section 2 contains the methods and materials applied in such study. Section 3 designates the investigational outcomes and discussion. The final section completes the GIC system.

2. Methods and Materials
The input fundus images are given to ranklet transform for decomposition. Then the decomposed image is given to entropy features like a sample, Shannon and approximate entropy. Finally, classification is made by using MLC. The workflow of the GIC system is shown in figure 1.

2.1. Ranklet Transform
The statistics are based on the estimation of Mann–Whitney–Wilcoxon, the rank-sum analysis. This rank-size functionality is selective and non-parametric. Ranklets have a similar response to hair wavelets as they share the same orientation, multi-scaling, and completeness pattern. In imaging, the robustness of outlier's detection and invariable monotonic processing features such as light, contrast
and gamma correction have become common. The ranklets are also used in watermarking [12] and mammogram [13]. Ranks have become popular. The ranklets are filled as non-filters in figure 2.

![Ranklet transform workflow](image)

**Figure 2.** Ranklet transform workflow

### 2.2. Entropy feature

Entropy is seen for one-dimensional and two-dimensional pattern identification systems as a possible feature. The product of an essential information fusion is entropy. Entropy based feature extraction is defined in two separate and groundbreaking ways. In this work, the sample entropy, Shannon entropy and approximate entropy are presented and discussed below [11].

#### 2.2.1. Sample entropy

Sample entropy applied to determine the complexity of time-series physiological signals also diagnose diseased states. Sample entropy has two benefits, its data length is independent, and its implementation is relatively problem-free. It can also take a logarithm of probabilities to the lower implementation values of template comparisons with itself. The signals are perceived more regularly than they are. The sample entropy does not contain such self-matches. Since sample entropy uses the correlation components directly, this is not an actual information calculation, but an approximation. The Sample entropy version, suggested by Costa and others, is multi-scalable [17].

#### 2.2.2. Shannon entropy

Shannon's entropy is essentially the sum of knowledge in a variable on a logical basis. More mundane is the amount of storage needed to store the variable, which can be interpreted intuitively to correlate to this variable's amount of data. Differential entropy is an information theory principle that started with a Shannon attempt to extend the idea of Shannon entropy to the continuous distribution of probabilities, the average surprise of a random variable.

#### 2.2.3. Approximate entropy

Approximate entropy is used in the statistics to quantify the regularity and impermissibility of fluctuations in the data from time series. Originally, regularity measured through exact regularity statistics, which focused mainly on various measures of entropy. However, exact entropy measurement involves large quantities of data and machine noise can significantly affect performance, so it is not feasible to apply these methods to experimental data.

### 2.3. MLC

The highest probability classifier is one of the most common remote sensing methods, where a pixel of the highest probability is categorized into the appropriate class. [15] The maximum probability classification assumes that the statistics are normally distributed for each class in each strip, and calculates the probability that a given pixel belongs to a particular class. A class with the highest likelihood is allocated to each pixel. MLC is also used in traffic signals and modulation signals [14].
Maximum probability is the process to find the value of one or more parameters for a particular statistical that maximizes the known distribution of probability. The highest probability estimate is indicated for a parameter [18].

3. Results and Discussion
The GIC structure's function is made by applying 50 fundus images selected from a private database [16]. The size of the image is 256x256 pixel in resolution. Figure 3 shows the normal and glaucomatous images in the database.

![Normal images](image1)

![Glaucomatous images](image2)

Figure 3. Sample fundus images in the database

The ranklet transform is applied to normal and glaucomatous images, and it produces the sub-band coefficients. These sub-band coefficients are extracted by entropy features like a sample, Shannon and approximate entropy separately. Finally, classification is made by using MLC. Table 1 to 3 shows the performance of the GIC system using entropy features and MLC.

| Sample entropy | MLC Classification (%) | Accuracy (%) | Sensitivity (%) | Specificity (%) |
|----------------|------------------------|--------------|-----------------|-----------------|
| **Rank 1**     |                        | 75           | 73              | 77              |
| **Rank 2**     |                        | 85           | 83              | 87              |
| **Rank 3**     |                        | 91           | 89              | 93              |
| **Rank 4**     |                        | 89           | 87              | 91              |
Table 2. Performance of GIC system using Shannon entropy feature and MLC

| Rank | Accuracy (%) | Sensitivity (%) | Specificity (%) |
|------|--------------|----------------|-----------------|
| 1    | 79           | 77             | 81              |
| 2    | 89           | 87             | 91              |
| 3    | 96           | 94             | 98              |
| 4    | 92           | 90             | 94              |

From the above table 1 to 3, the Shannon entropy feature with MLC produces the higher classification accuracy of 96%, and its sensitivity and specificity are 94% and 98% at 3rd rank. Also, sample entropy produces the classification accuracy of 91%, and its sensitivity and specificity are 89% and 93%. Finally, the approximate entropy produces the classification accuracy of 92%, and its sensitivity is 94%, and its specificity is 96% for GIC using MLC. Figure 3 shows the graphical representation of the GIC system.

Figure 4: Graphical representation of the GIC system

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4. Conclusion

A glaucoma image classification using entropy feature and maximum likelihood classifier is discussed in this work. Initially, the input fundus images are given to ranklet transform for decomposition. Then the entropy features like a sample, Shannon and approximate entropy are extracted separately. Finally, classification is made by using MLC for the GIC system. The highest classification precision is 96%.
also its sympathy plus particularity 94 % plus 98% for GIC system produced by Shannon entropy. The minimum classification accuracy is 91% obtained at sample entropy and MLC for the GIC system.

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