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Retinal Vein Occlusion – Analysis of Risk Factors using Neuro-Fuzzy Classifier

Dr. G. Lalli [1], Dr. D. Kalamani [2], N. Manikandaprabu [3]

[1.] *Associate Professor, Department of CA, Erode Sengunthar Engineering College, TN, (India)*

[2.] *Associate Professor, Department of Mathematics, Bharathiyar University PG Extension, TN, (India)*

[3.] *Assistant Professor, Department of ECE, Nandha Engineering College (Autonomous), TN, (India)*

ABSTRACT

Retinal Vein Occlusion occurs when one of the tiny retinal veins becomes blocked by a Blood Clot. It usually leads to a painless decrease in vision in one eye. Risk factors include High Blood Pressure, High Cholesterol Levels, Diabetes, Smoking and Raised Pressure in the Eye (Glaucoma). Treatment includes treating any possible risk factors and also treating any complications. The Feature Values of the Input Fundus Images of the Retina have been acquired from Messidor Database. The Colored Channels are also extracted. The Image Enhancement process is implemented using Histogram Equalization especially by Contrast Limited Adaptive Histogram Equalization (CLAHE). The Target of the Process is fixed as per the Guidelines of the Doctors in the particular field. The Features of the Images are extracted on basis of Texture Analysis using Gray-Level Co-Occurrence Matrix (GLCM). The Data are trained through Neuro-Fuzzy Classifier especially through Adaptive Neuro-Fuzzy Inference System (ANFIS). The Values '0' for Normal, '1' for Mild, '2' for Moderate and '3' for Severe are considered. The trained data are validated with Known Data Set. The Testing processes are carried out with unknown Data Set.

Key Words:Retinal Vein Occlusion, Fundus Image, Messidor Database, CLAHE, GLCM, ANFIS.

I. INTRODUCTION

Retinal Vein Occlusion is a blockage of the small veins that carry blood away from the retina. The retina is the layer of tissue at the back of the inner eye that converts light images to nerve signals and sends them to the brain.

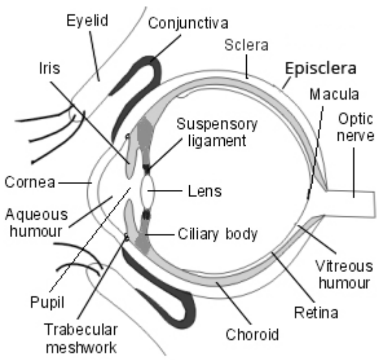

Fig. Anatomy of the Eye

Side view of the structure of the Eye-Retinal vein occlusion occurs when one of the tiny retinal veins becomes blocked by a blood clot. It usually leads to a painless decrease in vision in one eye. Risk factors include high blood pressure, high cholesterol levels, diabetes, smoking and raised pressure in the eye (glaucoma). Treatment includes treating any possible risk factors and also treating any complications. The View of Retinal Vein is also given below.

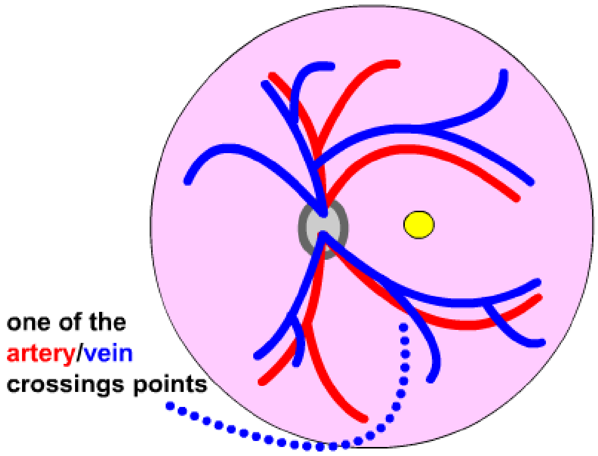

Fig. Retinal Vein

II. ASPECTS OF RETINAL VEIN OCCLUSION

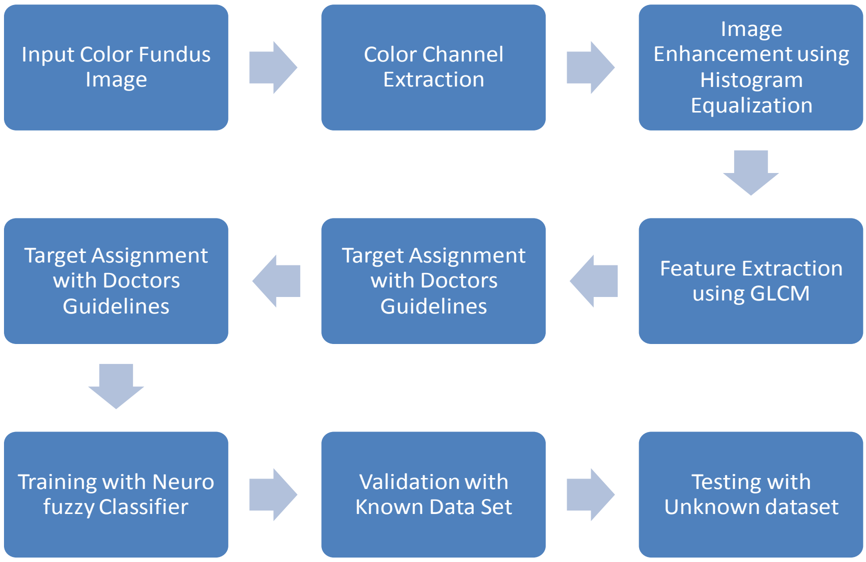

Fig. Aspects of Retinal Vein Occlusion

The Input Fundus Images have been acquired from the Messidor Database. The Colored Channels of the Fundus Images have been extracted through the MATLAB Processes and the Image is enhanced using Histogram Equalization. The necessary Features of the Images are extracted using Gray-Level Co-Occurrence Matrix (GLCM). The Target Assignment are fixed as per the requirement of the Physician and his/her guidelines. The Neuro-Fuzzy Classifier is used for Training the Data. The Trained Data are validated with Known Data Set and tested with Unknown Data Set.

III. IMAGE: GREEN AND GRAY CHANNELS EXTRACTION

The resized fundus image is converted in two different ways as separate processes. One is rgb-to-gray for gray channel extraction and another is RGB for green channel extraction.

IV.CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION (CLAHE)

In both way of separate serial processes, the contrast-limited adaptive histogram equalization (CLAHE) is used for enhancing the extracted image. "J = adapthisteq(I) enhances the contrast of the grayscale image I by transforming the values using CLAHE. CLAHE operates on small regions in the image, called *tiles*, rather than the entire image. Each tile's contrast is enhanced, so that the histogram of the output region approximately matches the histogram specified by the 'Distribution' parameter. The neighboring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited to avoid amplifying any noise that might be present in the image".

V. GLCM (GRAY-LEVEL CO-OCCURRENCE MATRIX)

Texture Analysis Using the Gray-Level Co-Occurrence Matrix (GLCM) A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (**GLCM**), also known as the gray-level spatial dependence matrix. It is used for image classification can also be referred as a co-occurrence distribution. It is defined over an image for the distribution of co-occurring values at a user-specific offset other hand it represents the distance as well as angular spatial relationship over an image sub-region of specific size. The GLCM is organized from a gray-scale image. The GLCM is calculates how over and over again a pixel with gray-level (grayscale intensity or Tone) value i occurs either horizontally, vertically, or diagonally to adjacent pixels with the value j. Textural Features are quite helpful for image classification.

Directions of Analysis with GLCM

1. Horizontal (00)
2. Vertical (900)
3. Diagonal:

a) Bottom left to top right (-450)
b) Top left to bottom right (-1350)

Denoted P0, P45, P90, & P135 Respectively.

Example: P90(i , j).

The efficient properties named autocorrelation, sum entropy, inverse-difference normalized, inverse-difference moment normalized and homogeneity of GLCM are used for classifying and extracting the gray level images and its' features respectively.

VI. NEURO-FUZZY CLASSIFIER

Neuro-Fuzzy Classifier always uses Adaptive neuro fuzzy inference system (ANFIS) as it's Classifier. ANFIS is a type of neural network based on Takagi–Sugeno fuzzy inference system. It integrates both neural networks and fuzzy logic principles. Hence, it has potential to capture the benefits of both the neural network and fuzzy logic in a single framework. Its inference system corresponds to a set of fuzzy IF–THEN rules that have learning capability to approximate nonlinear functions. Hence, ANFIS is considered to be a universal estimator.

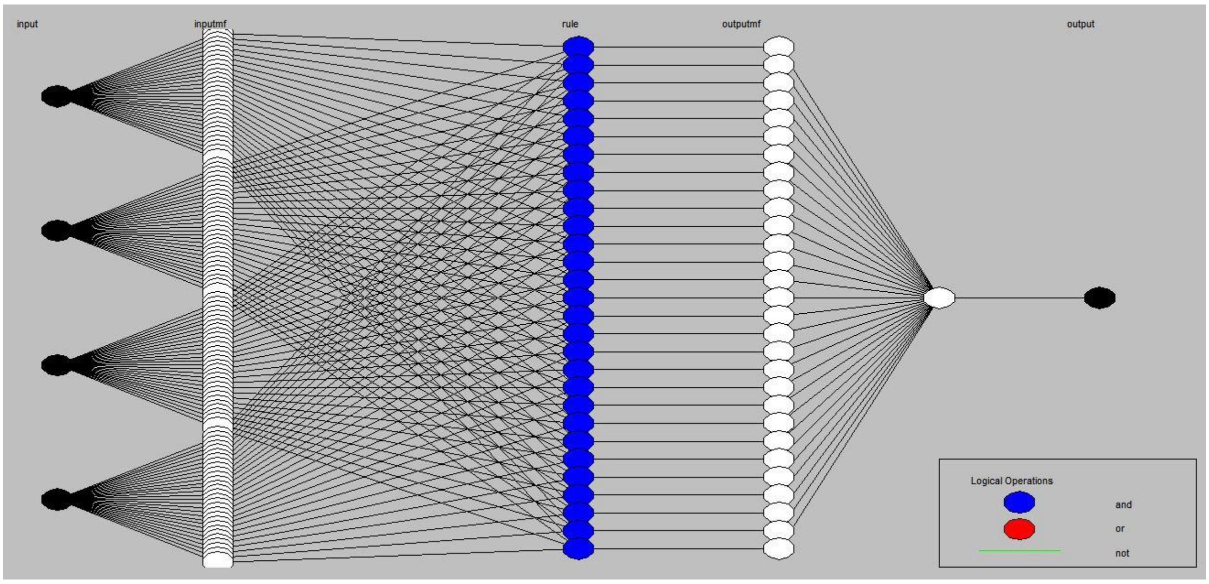

Fig. Neuro-Fuzzy Classifier – Logical Operations

VII.FEATURE VALUES FROM MESSIDOR DATABASE

The Features Values of the Fundus Images, which are acquired from the Messidor Database are classified as follows:

0:Normal

1:Mild

2:Moderate

3:Severe

The Training Data Set values are outputted through the System as follows.

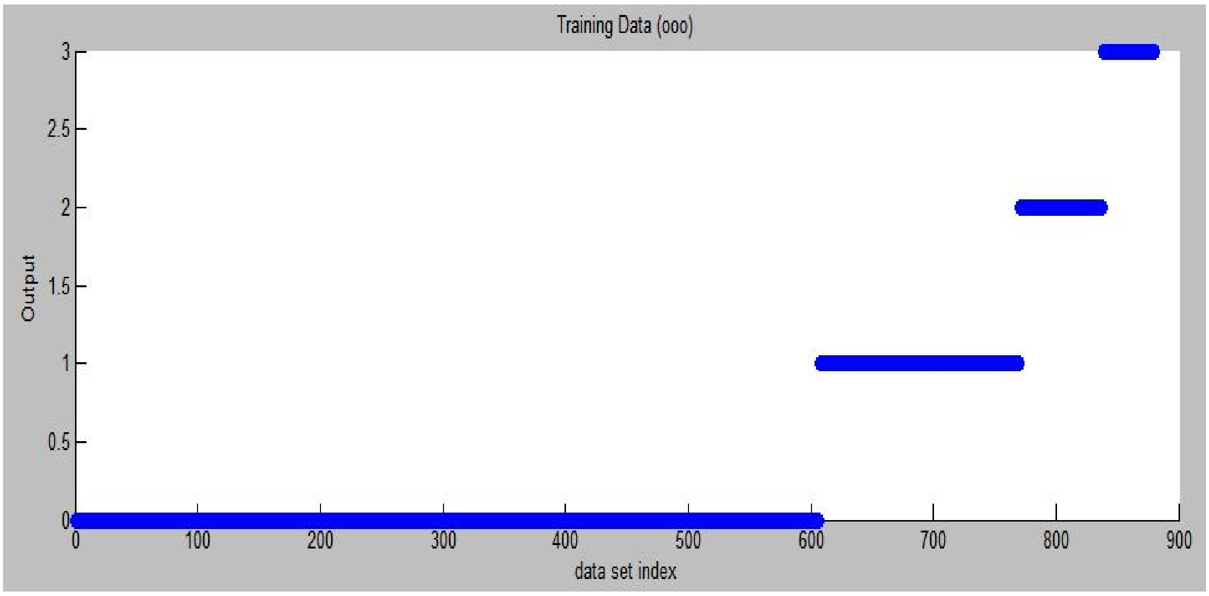

Fig. Neuro Fuzzy Classifier – Training Data

VIII. CLASSIFICATION OF FEATURE VALUES FROM MESSIDOR DATABASE

The Feature Values of the Retinal Fundus Images acquired from the Messidor Database are given below.

Table: Classification of Feature Values from Messidor Database

Sl. No.	Value-1	Value-2	Value-3	Value-4	Feature
1	0.034178	0.983511	0.421957	0.982912	0
2	0.058637	0.985828	0.308154	0.970727	0
3	0.02273	0.994818	0.444168	0.98867	0
4	0.065081	0.984057	0.355907	0.967518	0
5	0.020214	0.995766	0.417207	0.990056	0
6	0.042784	0.9756	0.322086	0.978608	0
7	0.040412	0.986714	0.339991	0.979798	0
8	0.044881	0.992767	0.3247	0.977826	0
9	0.040557	0.99309	0.336228	0.979826	0

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10	0.016558	0.996513	0.438309	0.99181	0
11	0.02654	0.992007	0.331754	0.986731	0
12	0.046983	0.983495	0.352747	0.976518	0
13	0.038247	0.970484	0.33671	0.980877	0
14	0.056331	0.985532	0.313793	0.9719	0
15	0.038952	0.993164	0.345341	0.980705	0
16	0.03762	0.993155	0.359164	0.981448	0
17	0.054581	0.990892	0.324504	0.972926	0
18	0.030483	0.994124	0.384643	0.984906	0
19	0.021977	0.995517	0.42673	0.989083	0
20	0.044591	0.986861	0.321506	0.977705	0
21	0.049719	0.987153	0.345813	0.975147	0
22	0.04864	0.991203	0.34449	0.976016	0
23	0.015798	0.992521	0.467047	0.992101	0
24	0.042527	0.989748	0.325121	0.978986	0
25	0.046986	0.989761	0.400018	0.97673	0
26	0.024533	0.988452	0.30566	0.9878	1
27	0.033226	0.989034	0.341438	0.983387	1
28	0.028573	0.989318	0.385775	0.985718	1
29	0.018746	0.992795	0.389643	0.990627	1
30	0.023299	0.9914	0.380927	0.988351	1
31	0.014933	0.992773	0.460398	0.992534	1
32	0.021849	0.989826	0.431947	0.989076	1
33	0.027273	0.990246	0.383854	0.986367	1
34	0.027075	0.987546	0.422554	0.986462	1
35	0.011971	0.994596	0.458165	0.994015	1
36	0.073463	0.984312	0.330379	0.963724	1
37	0.034787	0.992425	0.428457	0.982743	1
38	0.045089	0.97637	0.347996	0.977456	1
39	0.0409	0.985063	0.364918	0.979584	1
40	0.030653	0.987355	0.410346	0.984683	1
41	0.043055	0.989744	0.326295	0.978473	1
42	0.026226	0.987571	0.411953	0.986887	1
43	0.013885	0.993637	0.450743	0.993058	1
44	0.024126	0.992884	0.332315	0.988181	1
45	0.016035	0.993357	0.417547	0.991984	1

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46	0.037777	0.988907	0.323373	0.981133	1
47	0.054026	0.984955	0.316453	0.972987	1
48	0.067463	0.981726	0.319932	0.966375	1
49	0.022808	0.995155	0.449177	0.988791	1
50	0.05202	0.986368	0.304316	0.974048	1
51	0.038739	0.990487	0.363942	0.980664	2
52	0.035586	0.990389	0.333886	0.98221	2
53	0.035915	0.984695	0.362666	0.982043	2
54	0.019811	0.993357	0.359242	0.990112	2
55	0.036778	0.988319	0.33672	0.981613	2
56	0.030461	0.989429	0.371012	0.984771	2
57	0.016893	0.992015	0.444665	0.991558	2
58	0.048379	0.988919	0.348891	0.975959	2
59	0.047911	0.990385	0.362309	0.976094	2
60	0.033744	0.992624	0.410378	0.983153	2
61	0.047246	0.989154	0.326917	0.976589	2
62	0.015914	0.993302	0.429603	0.992119	2
63	0.054436	0.985478	0.331509	0.973029	2
64	0.02224	0.995129	0.415365	0.988943	2
65	0.01001	0.997774	0.471721	0.995009	2
66	0.075775	0.960308	0.329817	0.962121	2
67	0.018951	0.993842	0.377241	0.990527	2
68	0.091042	0.975844	0.314657	0.954495	2
69	0.048078	0.985409	0.324817	0.975971	2
70	0.013936	0.997076	0.443076	0.993124	2
71	0.015617	0.996791	0.437922	0.992297	2
72	0.057652	0.987799	0.323726	0.971402	2
73	0.0329	0.992245	0.423264	0.983567	2
74	0.033016	0.992458	0.42358	0.983553	2
75	0.036086	0.989893	0.319279	0.98223	2
76	0.087485	0.975759	0.300403	0.956331	3
77	0.025092	0.989283	0.406614	0.987474	3
78	0.023909	0.994805	0.44379	0.98821	3
79	0.007233	0.996474	0.478932	0.996384	3
80	0.056243	0.971239	0.352002	0.971902	3
81	0.03762	0.982732	0.414637	0.981238	3

82	0.030465	0.993719	0.43351	0.985061	3
83	0.016012	0.993302	0.424796	0.991994	3
84	0.025737	0.990824	0.372157	0.987133	3
85	0.064291	0.98293	0.310714	0.967872	3
86	0.03776	0.989005	0.334594	0.981131	3
87	0.035368	0.989838	0.324136	0.982316	3
88	0.046624	0.988558	0.321699	0.976688	3
89	0.017583	0.992643	0.420973	0.991209	3
90	0.030502	0.99427	0.376507	0.984955	3
91	0.036088	0.993141	0.379964	0.982076	3
92	0.033992	0.982027	0.364668	0.983004	3
93	0.018276	0.990684	0.422948	0.990862	3
94	0.053538	0.970412	0.329695	0.973231	3
95	0.017033	0.992046	0.443157	0.991484	3
96	0.019915	0.992105	0.400797	0.990045	3
97	0.024979	0.994499	0.433727	0.987526	3
98	0.053676	0.986974	0.348397	0.973233	3
99	0.019942	0.995705	0.449954	0.990126	3
100	0.065023	0.983861	0.343175	0.967511	3

IX. SYSTEM PERFORMANCE EVALUATION

The Evaluation Details of the System's Performance is given below.

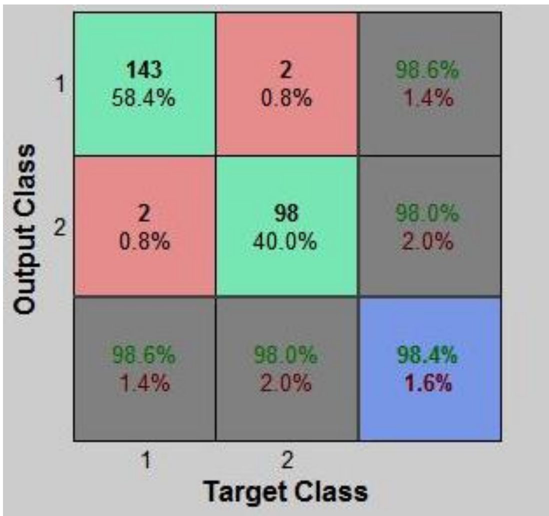

Fig. System Performance Evaluation-1

Percentage of Trained Data: 98.4%

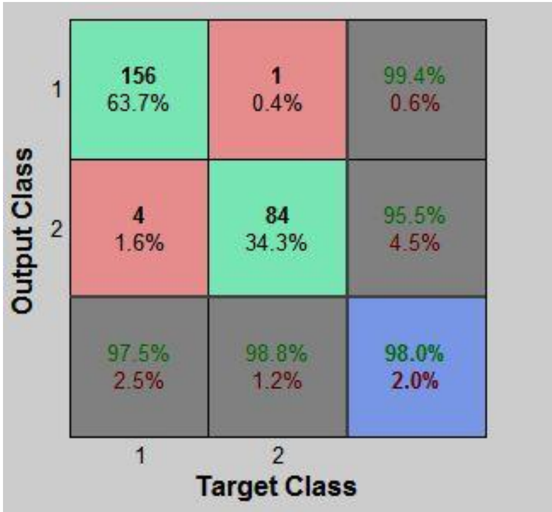

Fig. System Performance Evaluation-2

Percentage of Tested Data: 98.4%

X. CONCLUSION

The Feature Values of the Input Fundus Images of the Retina are trained through Neuro-Fuzzy Classifier. The Values ‘0’ for Normal, ‘1’ for Mild, ‘2’ for Moderate and ‘3’ for Severe are identified through this analysis for the treatment includes treating any possible risk factors of the Retinal Vein and also treating any complications.

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