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Differential Diagnosis of Eye Diseases Based on Fuzzy Cognitive Map

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Abstract: *The prevalence of eye diseases and its attendant effects which lead to blindness motivated an investigation into how diagnoses are undertaken. One startling revelation is the dearth of optical experts to cope with the increasing cases of eye diseases in clinics. This further prompted the design of a differential diagnosis tool for the purpose of aiding opticians in their assignment of diagnosis of eye diseases. Conflicting symptoms cause a lot of confusion to medical experts especially the inexperienced ones. In an attempt to carry out this task, two opticians were consulted independent of one another to assist in weighting 17 symptoms of 6 confusable eye diseases. The symptoms were weighted with respect to their causal relationship to one another and the 6 diseases. In addition to this, the opticians assisted in giving diagnostic results of 20 hypothetical cases independent of one another. Armed with this information and datasets, a Fuzzy Cognitive Map (FCM) was designed for the 17 symptoms and 6 diseases. From the FCM, an adjacency matrix was constructed. To obtain optimal weights through the links of the maps, a training session was undertaken using Hebbian learning rule. With all these, the 20 hypothetical cases were subjected to train the map. Results obtained from the exercise were compared with that obtained from the two opticians. A correlation of 0.65 was observed with the results of the first optician while a correlation of 0.45 was seen from that of the second optician. A novel feature of the differential diagnosis using the FCM methodology is the ability to give varying degrees of diagnosis of the main ailment and in addition that of an associated ailment. In doing so, the optician who is the ultimate user of the system could choose which of them to treat first maybe considering the severity of the ailment and how life threatening is one to another.*

Keywords*: Fuzzy logic, Cognitive map, Differential diagnosis, Hebbian Learning, Eye Diseases.*

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I. Introduction

The eye is one of the vital organs of the body and serves as an organ of sight. Its position in the body exposes it to so many dangers making it vulnerable to diseases. A diseased eye is a nightmare to the body and one of the major causes of regular visits to the hospitals. Ironically, most times the visit is made at an advanced stage of the disease when self medications had failed. Misdiagnosis of the eye diseases due to conflicting symptoms often lead to complication of the problem and often to blindness. In some cases it causes permanent problem that requires the use of eye-glasses all through the life time of the patient.

The inability of an optician to differentiate one symptom of eye diseases from the other is further complicated by the inability of the patient to explain to the optician exactly how he (the patient) feels. The ambiguity in expression leads the optician to confusion and subsequently misdiagnosis of the disease. Some misdiagnoses complicate the problems of the patient as such diagnoses will cause wrong therapy for the patient. The therapy rather than relief the pains could cause grief.

Medical diagnostic system deals with eliciting both vital and non-vital information from the patient which the medical doctor will try to decipher such information and relate with the structured knowledge of the suspected disease. Aside from this information, the laboratory results can also be used to establish a relationship of the symptoms and the suspected disease. In effect, there are relationship and interrelationship with causal influences. All these assist the medical doctor in taking a decision about a patient. The cognitive ability of the medical doctor to map the signs and symptoms elicited from the patients as the causal effect of the suspected disease enable the medical doctor to confirm the presence or absence of the disease in the patient.

Cognitive maps according to Eden (2004) are collection of nodes linked by some arcs or edges. The nodes represent concepts or variables relevant to a given domain. A causal relationship is established between the nodes through the arcs or edges. The cause could be positive (excitatory) or negative (inhibitory) and where there is no causal effect the link represents null or zero. In the positive effect, the source node is said to excite the target node meaning that an increase in the value of the source node leads to a corresponding increase in the value of the target node. Corollary, in the negative effect the source is said to inhibit the target node, showing

that an increase in the value of the source node leads to a corresponding decrease in the value of the target node. In Fuzzy Cognitive Map (FCM), the causal relationship is not discrete but continuous thereby expressing the degree of relationship between two concepts or nodes. The effect of change in a concept can affect other nodes including the node that initiates the change. There is a feedback making FCM to be dynamic. The strength of connection between two nodes is taken in the range of values between -1 and 1 where -1 represents a complete negative and 1 represents a complete positive while 0 shows no causal effect and the other values represent the degree of causal relationship. Kosko (1986) describes FCM by a connection matrix E whose elements are the connection strengths (or weights) e_{ij}. The element in the i_{th} row and j_{th} column of matrix E represents the connection strength of the link directed out of node C_i into C_j .

The value of each concept is influenced by the values of the connected concepts with the appropriate weights and by its previous value. So the value A_i for each concept C_i is calculated as shown in equation 1.1

$$A_i = f\left(\sum_{\substack{j=1 \\ j\neq i}}^{n}\right)(A_j W_{ji}) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (1.1)$$

where A_i is the activation level of concept C_i

A_j is the activation level of concept C_j

W_{ji} is the weight of the interconnection between concepts C_i and C_j

f is the threshold function which limits unbounded inputs to a range.

This study uses FCM to carry out the differential diagnosis of 6 diseases using datasets already diagnosed by 2 opticians independent of each other. Section 2 of the study presents review of related literature while the design methodology is presented in Section 3. The experiment of the study undertaken in MATLAB is reported in Section 4 with the discussion of the results obtained presented in Section 5. The conclusion of the research and some recommendations made are presented in Section 6.

II. Literature

An integrated breast cancer risk assessment and management model based on FCM was presented in Subramanian (2015). A two-level model was designed with level 1 modeling the demographic risk profile and level 2 modeling the features of the screening mammography concerning normal, benign and malignant cases. Data-driven non-linear Hebbian learning algorithm was used to train the model which predicts the degree of cancer risk based on the mammographic image features. The results of the two models were combined to determine the degree of overall risk of cancer. 70 real cases of mammogram images were used for the level 2 model with 94.3 accuracy while 36 of the 40 patients comply to the Tyrer-Cazick model of classification.

In Georgopoulos et al (2003), a FCM approach to differential diagnosis of Specific Language Impairment (SLI) was attempted. The study was motivated by the hypothesis that specific language impairment cases are confused with severe cases of dyslexia and mild cases of autism. 4 case studies were culled from the literature and investigated using Hebbian learning rule and triangular membership function. It was revealed that each node (concept) converges at a final value with the maximum value taken as the most probable diagnosis. The correct diagnosis was conducted for all the four cases with the case of dyslexia having marginal difference from that of SLI. This was attributed to the fact that the diagnosis was a severe diagnosis. The procedure was repeated 10000 times with random values representing 10000 different cases, the results of those repetitions tarry with the 4 cases earlier carried out, thereby confirming the hypothesis.

In Baykasoglu and Durmusoglu (2014), a hybrid of FCM and Multi-criteria Decision Method (MCDM) for private primary school assessment using DEMATEL based on ANP was designed. The study addressed the problem of choice of primary schools of parents to their children. 28 factors were considered and pairwise comparison of the factors were conducted to form the super matrix which feed the FCM model with weights linking the nodes to produce causal effects. 6 schools in Turkey were evaluated and it was revealed that a school labeled 'E' appeared the most favourable of the 6 schools with the cost benefit ratio of 0.14.

A hybrid of Case-Based Reasoning (CBR) and Fuzzy Decision Tree (FDT) for medical data classification was designed in Fan et al (2011). 345 datasets of liver disorder and 569 datasets of breast cancer were gathered from UCT library. The datasets were clustered using K-means algorithm. The study combines genetic algorithm and FDT to develop a classification model. Results obtained were compared with the results of the conventional classification tools such as KNN, SVM and Naïve Bayes and was discovered that the CBR-FDT has a high accuracy ratio of 0.904 followed by SVM (0.776), FDT has a worst ratio of 0.683 for liver disorders. For breast cancer the same trend was followed by CBR-FDT having 0.989 followed with SVM (0.981) and FDT (0.902).

Lopes et al (2013) developed a FCM for the differential diagnosis of alterations in urinary eliminations using a nursing approach. 6 confusable diagnoses were considered with 39 signals associated with such diagnosis. FCM was modeled to test the sensitivity and specificity with respect to nurses (experts) opinion.

Under estimation and over estimation of the diagnoses were considered and results of overestimation showed an excellent agreement with experts' opinion while under estimation shows moderate agreement. FCM was observed to show high sensitivity and specificity of 0.95 and 0.92 respectively.

Papageirgiou et al (2015) developed a risk management model for familial breast cancer using FCM method. The non-linear Hebbian learning technique was used to learn causal weights from 40 patient records with concentration on family history, personal history and medical history of the patients. Comparison of the results obtained was made with that of standard models which estimate the risk of familial breast cancer among women. 95% diagnostic accuracy representing 38 of the 40 cases was recorded showing a concordance with the comprehensive risk evaluation tool based on Tyre-Cuzik model. Comparison was also done with a similar study's result in Subramanian (2015) and found to have a better output by 5% based on the confusion matrix.

Bhutani et al (2015) performed classification on the lenses datasets using fuzzy inference system (FIS) and FCM. The datasets had 4 attributes namely; age, spectacle prescription, astigmatic and tear production rate. With 24 datasets, training and testing was undertaken showing that FIS has 100% classification accuracy. Douali et al (2014) designed a DSS based on clinical guidelines and made comparison between a case-based FCM and Bayes networks. 174 anonymous patients' datasets from some European hospitals comprising 80 males and 94 females were used in the study. A Clinical Practice Guideline (CPG) was used as a source of knowledge of Urinary Tract Infection (UTI) diagnosis which aid to derive a decision tree. CBR-FCM was developed using the tools of semantic web with the CPG assisting to express the fuzzy rules. 98% of the 174 patients were in full agreement with the guideline when analysed with CBR-FCM while 86% were in full agreement when analysed with Bayesian network. Further analysis was done using the Receiver Operating Characteristic (ROC) where the CBR-FCM model covers 0.88 area under curve and Bayesian covers 0.69 area.

Sarabai and Arthi (2016) classified breast cancer using improved FCM with Cat Swarm Optimization and Neural Network (CSONN). Neural network was employed to train the datasets using the Cat Swarm Optimization (CSO) technique. The Optimal Brain Damage (OBD) approach was used to prune the network structure by eliminating the poor weights thereby increasing the network performance. Several MRI breast cancer images preprocessed with adaptive median filter were used for the training. The C-means clustering method assisted in segmenting the images while FCM was used in the actual classification into malignant and normal. The classification accuracy using different methods shows FCM without pruning (86%), CSONN (88.3%) and CSOFCM OBD pruning (98.3%).

Natarajan et al (2016) developed a hybrid learning of FCM for sugarcane yield classification. The data driven nonlinear Hebbian learning rule was used to generate weights from the initial weights generated by experts. Genetic algorithm used the generated weights and improved upon it to give optimal weights. These optimal weights were then used to construct a FCM using 20 concepts of influence on yield. The best classification was obtained with a learning rate of 0.001 and a learning momentum of 0.98 to obtain a classification accuracy of 0.92. The hybrid approach yielded an accuracy of 94.7% compared to FCM-GA (93.4%) and FCM-DDHNL (92.1%). A comparison with other machine learning approaches like Multi Layer Perceptron (MLP) and random tree showed that the hybrid approach outperformed them.

Obot and Inyang (2015) developed an intelligent clustering based methodology for confusable tropical diseases diagnosis and monitoring. The study was motivated by the misdiagnosis and wrong diagnoses occasioned by conflicting symptoms of malaria, typhoid fever, hepatitis and Urinary Tract Infection (UTI). 67 diagnosed cases were collected from some hospitals and trained using Adaptive Neuro Fuzzy Inference System (ANFIS). The symptoms of these 4 diseases were found to overlap leading to confusion on their diagnoses by inexperienced physicians. The inference engine of the system was driven by fuzzy C-means clustering algorithm and ANFIS. Results show that the patients suffered from varying degree of severity of each of the diseases. The disease having the highest degree of severity was recommended for treatment and others with competing degrees to be treated based on the most life threatening case. Partition Coefficient (PC) and partition Entropy (PE) were used to validate the fuzzy clusters with PC (0.396) and PE (0.795) indicating strong existence of partitions.

Georgopoulos and Stylios (2005) developed an augmented FCM supplemented with CBR for advanced medical decision support. In the study, the approaches used for CBR and FCM were combined to manage implicit knowledge. Situations where there were patients data to be captured into the system present very rare configuration of symptoms where most of the nodes of the FCM would not be active. Using the KNN algorithm the captured case was compared with the cases in the case base which was then passed into FCM to perform the final diagnosis. This technique was applied to speech and language pathology datasets and found to be satisfactory in its diagnosis.

Papageorgiou, E. I (2011) developed an augmented FCM based on fuzzy rule extraction method for decisions on medical informatics. Knowledge is extracted from the data gathered to construct the FCM using a case study of radiation therapy. Results obtained were compared to the traditional FCM results and found to covary.

Walia et al (2015) developed a decision support system for tuberculosis diagnosibility. 77% accuracy was obtained from the system generated responses compared to the demographic data generated by domain experts.

Fraccaro et al (2015) reviewed clinical decision support methodologies with the objectives of introducing clinicians and policy makers to the most commonly computer based methodologies employed to build decision models for clinical decisions. CDSS are categorized into passive, semi active and active systems.

Kannapan etal (2011) proposed a FCM trained with non-linear Hebbian learning algorithm to predict autistic disorder. With 40 datasets gathered from domain experts, the system was able to classify to have a 79.9% accuracy compared to that classified by domain experts.

III. Design

Several eye diseases present conflicting symptoms, 6 of such diseases were selected for this study as presented in Figure 1.

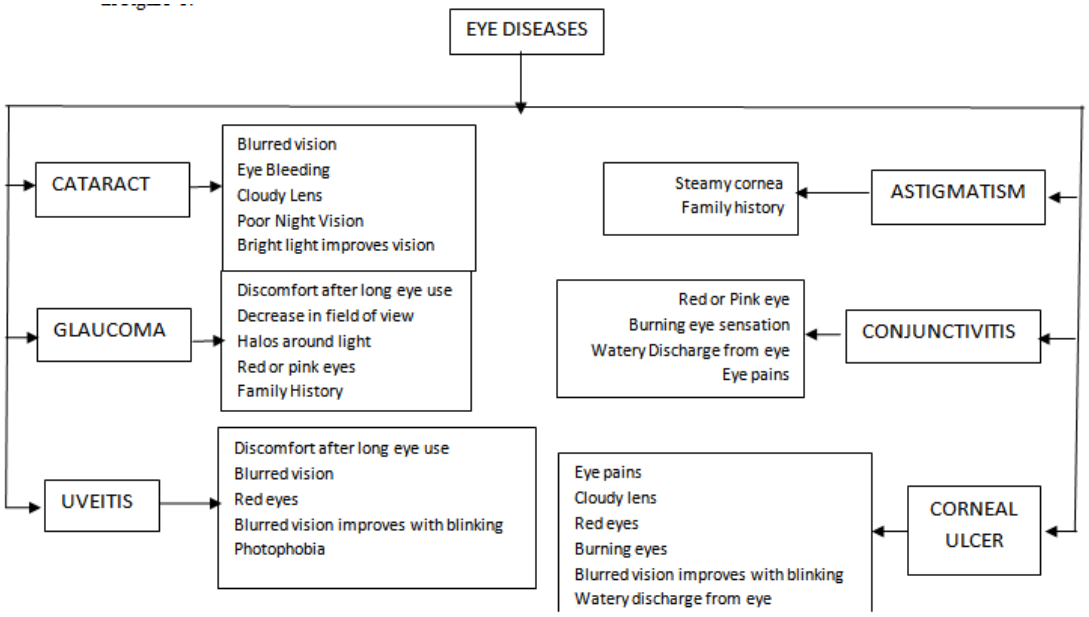


Figure 1: Schematic representation of Eye Diseases and their symptoms

Notice from Figure 1 that most symptoms appear in more than one disease for example a symptom like blurred vision appears for cataract, uveitis, and corneal ulcer while red eye appears for all the six diseases except astigmatism.

3.1 Data Collection

With the assistance of 2 ophthalmologists data for the study were collected. The ophthalmologists identified all the concepts, stated the influence of each concept on the other and as well assigned fuzzy weights to each interconnection in the FCM. The various concepts, their influences as well as their weights are specified in the Table 2 while Table 1 shows the name and meaning of each concept.

Table 1: Concepts and their meanings

CONCEPT	MEANING	CONCEPT	MEANING
Concept 1	Pains in the eyes	Concept 13	Halos around light
Concept 2	Red or Pink eye	Concept 14	Poor night vision
Concept 3	Conjunctivitis	Concept 15	Cataract
Concept 4	Burning eye sensation	Concept 16	Cloudy lens
Concept 5	Blurred vision improves with blinking	Concept 17	Bright light improves vision
Concept 6	Corneal Ulcer	Concept 18	Astigmatism
Concept 7	Swollen eyelids	Concept 19	Family history of the eye disease
Concept 8	Photophobia	Concept 20	Eye bleeding
Concept 9	Uveitis	Concept 21	Decrease in peripheral field of view
Concept 10	Watery discharge from eye	Concept 22	Steamy cornea
Concept 11	Blurred vision	Concept 23	Discomfort after long eye use
Concept 12	Glaucoma		

Note that concepts 3, 6, 9, 12, 15 and 18 represent the diseases while others represent the symptoms of the diseases

TABLE 2: Tabulation of inter-concepts influences

CONCEPT	CODE	CONCEPT INFLUENCED	CODE	WEIGHT
Pains in the eye	C1	Corneal ulcer Conjunctivitis Uvietis	C6 C3 C9	0.9 0.6 0.4
Red or pink eyes	C2	Conjunctivitis Uvietis Corneal ulcer Glaucoma	C3 C9 C6 C12	1.0 0.8 0.4 0.3
Irritation, itchy, scratchy or burning eye sensation	C4	Conjunctivitis Corneal ulcer	C3 C6	1.0 0.5
Blurred vision improves with eye blinking	C5	Uvietis Corneal ulcer	C9 C6	1.0 0.4
Swollen eyelids	C7	Conjunctivitis	C3	0.2
Sensitivity to light (photophobia)	C8	Uvietis	C9	0.9
Watery discharge from eye	C10	Conjunctivitis Corneal ulcer	C3 C6	0.9 0.5
Blurred vision	C11	Cataract Corneal Ulcer Uvietis	C15 C6 C9	0.9 0.4 0.4
Floaters in eye, flashes of lights, halos around light	C13	Glaucoma Cataract	C12 C15	1.0 0.6
Poor night vision	C14	Cataract Astigmatism	C15 C18	0.7 0.6
Cloudy substance formed in front of eye lens	C16	Corneal ulcer Cataract	C6 C15	0.9 0.8
Bright light improves vision	C17	Cataract	C15	0.8
Family history of the eye problem	C19	Glaucoma Astigmatism	C12 C18	0.5 0.7
Bleeding in front part of the eye	C20	Cataract	C15	0.4
Decrease in the peripheral field of view	C21	Glaucoma	C12	1.0
Steamy appearing cornea of eye	C22	Astigmatism	C18	0.8
Discomfort after long concentrated use of eye	C23	Uvietis Glaucoma	C9 C12	0.8 0.4

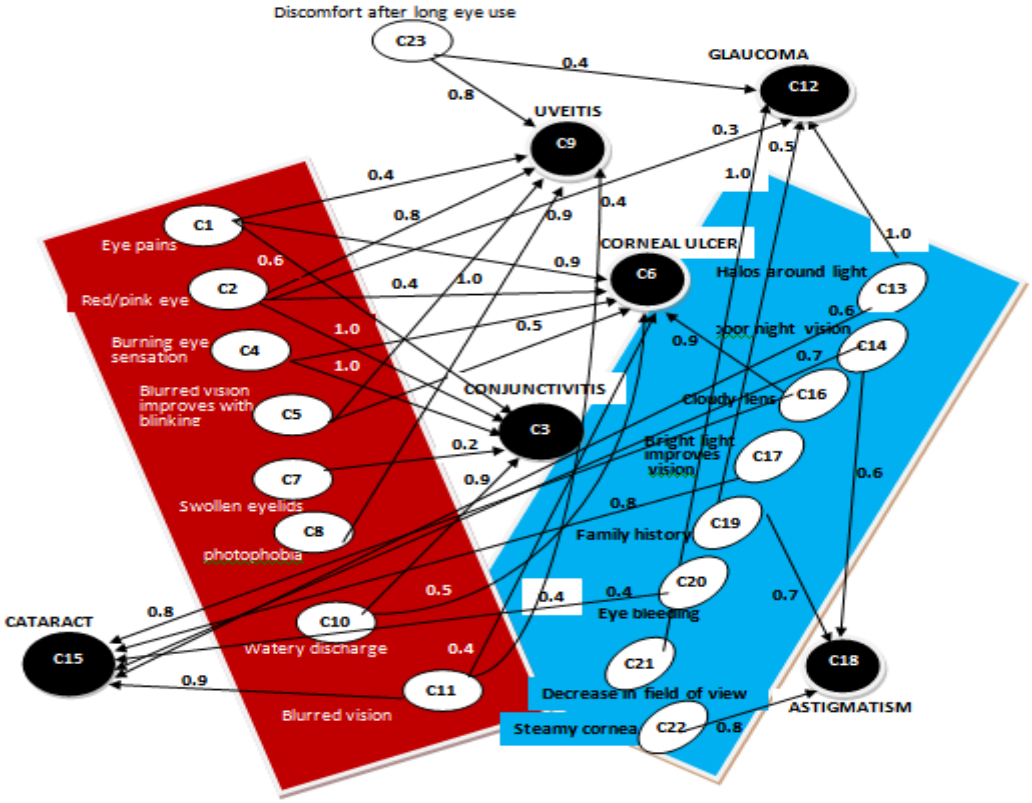
The following sets of data presented in Table 3 were collected from the hospital

Table 3: Datasets collected from the Hospital

PATIENT NUMBER	EYE PAINS	REDPINK EYE	BURNING EYE SENSATION	BLURRED VISION IMPROVES WITH BLINKING	SWOLLEN EYELID	PHOTOPHOBIA	WATERY DISCHARGE FROM EYE	BLURRED VISION	HALOS AROUND LIGHT	POOR NIGHT VISION	CLOUDY LENS	BRIGHT LIGHT IMPROVES VISION	FAMILY HISTORY	EYE BLEEDING	DECREASE IN FIELD OF VIEW	STEAMY CORNEA	DISCOMFORT AFTER LONG EYE USE	DIAGNOSIS	
																		OPTICIAN 1	OPTICIAN 2
1	0	.3	0	0	0	0	0	0	1	0	0	0	.5	0	1	0	.4	GLA 0.9	GLA 0.6
2	0	0	0	0	0	0	0	0	0	.6	0	0	.7	0	0	.8	0	AST 0.6	AST 0.5
3	0	.7	0	0	0	0	.6	0	0	0	0	0	.5	0	0	0	0	CON 0.6	CON 0.7
4	.2	0	0	0	.7	0	0	0	0	.8	0	0	0	0	0	0	.9	UVE 0.4	UVE 0.5
5	.6	1	1	0	.2	0	.9	0	0	0	0	0	0	0	0	0	0	CON 0.9	CON 0.7
6	.1	.3	.4	0	0	0	0	.9	0	0	0	0	.4	.9	0	0	0	CAT 0.5	UVE 0.4
7	.9	.5	0	0	0	0	0	.4	0	0	.6	0	0	0	0	0	0	COR 0.7	COR 0.7
8	0	0	.4	0	0	.9	0	0	0	0	.9	0	.9	0	1	0	0	GLA 0.6	GLA 0.5
9	.1	0	.2	0	0	0	0	0	.9	0	0	0	0	.7	0	0	0	GLA 0.4	CAT 0.3
10	0	0	.9	0	0	0	0	0	0	0	1	0	0	0	0	0	.6	COR 0.6	COR 0.6
11	1	0	.9	0	0	0	0	1	0	0	1	0	.9	0	0	0	0	GLA 0.8	GLA 0.5
12	0	0	0	0	0	0	0	.6	0	0	0	0	0	.9	0	0	0	CAT 0.6	CAT 0.6
13	.7	0	0	.1	0	.1	0	0	.1	0	0	0	.2	0	0	0	0	COR 0.5	COR 0.7
14	0	0	0	0	0	0	0	.6	0	.9	0	0	0	0	0	0	0	UVE 0.7	UVE 0.4
15	0	0	0	0	.9	0	0	.6	0	.4	0	0	0	0	0	.6	0	GLA 0.7	GLA 0.3
16	0	.8	.6	0	.9	0	.7	.6	0	0	0	0	0	0	0	0	0	COR 0.7	COR 0.8
17	0	0	.8	0	.9	0	0	0	0	0	0	.2	0	0	0	0	0	CON 0.8	COR 0.8
18	1	0	0	0	0	0	0	.8	0	0	.9	0	0	0	0	0	0	UVE 0.8	UVE 0.6
19	.4	.8	0	1	0	.9	0	.4	0	0	0	0	0	0	0	0	.8	COR 0.6	COR 0.5
20	0	0	0	0	.9	0	0	0	0	0	0	0	0	0	0	.9	0	AST 0.7	AST 0.6

3.2 Building the Model

The FCM as shown in Figure 2 has 23 concepts (6 diseases and 17 symptoms). Diseases are dark coloured while symptoms are not coloured. The weighted edges indicate the direction of influence between the source and the target concepts.



3.3 Adjacency Matrix

In the adjacency matrix shown in Table 4, the number on the rows and columns represent the concepts, while the intersection of the row and column represents the degree of influence of the row number (source concept) and the column number (target concept). For example, the intersection of row 4 and column 2 is 0 which shows that there is no degree of influence between concept 4 and concept 2 but the intersection between row 1 and column 9 is 0.4 which shows 40% influence of concept 1 on concept 9.

Table 4: Adjacency Matrix

C	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1	0	0	.6	0	0	.9	0	0	.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	1	0	0	.4	0	0	.8	0	0	.3	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	1	0	0	.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	.4	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	.9	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	.9	0	0	.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	.4	0	0	0	0	0	0	0	0	.9	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	1	0	0	.6	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.7	0	0	.6	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	.9	0	0	0	0	0	0	0	0	.8	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.4	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	.5	0	0	0	0	0	.7	0	0	0	0	0

20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.4	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.8	0	0	0	0	0
23	0	0	0	0	0	0	0	0	.8	0	0	.4	0	0	0	0	0	0	0	0	0	0	0

3.4 Hebbian Learning Rule

Hebbian learning rule is biologically plausible and it is an unsupervised learning technique. It is a non-linear learning algorithm and very suitable for connectionism such as FCM. According to Goswami (2012) the learning signal is equal to the neuron's output and given in equations 3.1-3.3 as:

$R = f(W_i^t x)$ ……. (3.1)

The increment of the weight vector becomes

$\Delta W_t = cf(W_i^t x)x$ …….. (3.2)

The single weight adjustment using the increment becomes

$\Delta W_{ij} = cf(W_i^t x_i)x_j$ …….. (3.3)

Algorithm for implementing the Non-Linear Hebbian Learning Rule

Step 1: Accept input

Step 2: Multiply the input (1X23) matrix by the adjacency matrix (23X23)

Step 3: Invert the product of step 2 to a row matrix and multiply it with the input vector and obtain a scalar quantity (+ve, -ve, 0)

Step 4: Multiply the output of step 2 by an identity matrix to obtain another matrix (23X23)

Step 5: Add or subtract (depending on the result of step 3) the adjacency matrix and the product of matrix (i.e result of step 4). If the result of step 2 is zero, then new matrix equals old matrix.

Step 6: Repeat step 1 to 5 as long as the inputs are available

Step 7: The results obtained becomes the standard adjacency matrix (i.e the weight matrix that is used to diagnose new cases).

3.5 Simulation

Considering the following inputs where concepts 2 (Red or pink eye), concept 10 (Watery discharge from eyes) and concept 19 (Family history) are activated respectively with the following values 0.7, 0.6 and 0.5.

Thus A_i = [0 0.7 0 0 0 0 0 0 0 0.6 0 0 0 0 0 0 0 0 0.5 0 0 0 0] where A_i = initial state vector.

Multiplying A_i with the adjacency matrix in Table 4 yields the following values

Conjunctivitis:

(0*0.9)+(0.7*1)+(0*0)+(0*1)+(0*0)+(0*0)+(0*0.2)+(0*0)+(0*0)+(0.6*0.9)+(0*0)+(0*0)+(0*0)+(0*0)+(0*0)+(0*0)+(0*0)+(0*0)+(0.5*0)+(0*0)+(0*0)+(0*0)+(0*0) = 1.24

Passing through the transfer function $f = \frac{1}{1+e^{-x}}$ where x = 1.24

$= \frac{1}{1+e^{-1.24}} = 0.78$

Therefore Conjunctivitis = $\frac{0.78-0.5}{0.5} * 100 = 0.56$

Uveitis:

(0*0.4)+(0.7*0.8)+(0*0)+(0*0)+(0*1)+(0*0)+(0*0)+(0*0.9)+(0*0)+(0.6*0)+(0*0)+(0*0)+(0*0)+(0*0)+(0*0)+(0*0)+(0*0)+(0*0)+(0.5*0)+(0*0)+(0*0)+(0*0)+(0*0) = 0.56

Passing through the transfer function $f = \frac{1}{1+e^{-x}}$ where x = 0.56

$= \frac{1}{1+e^{-0.56}} = 0.6$

Therefore Uveitis = $\frac{0.6-0.5}{0.5} * 100 = 0.2$

Astigmatism

(0*0)+(0.7*0)+(0*0)+(0*0)+(0*0)+(0*0)+(0*0)+(0*0)+(0*0)+(0.6*0)+(0*0)+(0*0)+(0*0)+(0*0.6)+(0*0)+(0*0)+(0*0)+(0*0)+(0.5*0.7)+(0*0)+(0*0)+(0*0.8)+(0*0) = 0.35

Passing through the transfer function $f = \frac{1}{1+e^{-x}}$ where x = 0.35

$= \frac{1}{1+e^{-0.35}} = 0.58$

Therefore Astigmatism = $\frac{0.58-0.5}{0.5} * 100 = 0.16$

4.0 Experiment

As an example, if the state vector is activated such that concept number 1,5 and 16 are activated with the following initial weights:
A_{ij} = [0.9 0 0 0 0.4 0 0 0 0 0 0 0 0 0 0 0.7 0 0 0 0 0 0 0] as shown in Figure 5

In implementing the initial state vector, a row vector of 23 elements is declared using the MATLAB command A = zeros(1,23). This implies that all the 23 concepts are set to zero by default which the user will later change the values of those cells that are considered activated. The learning rate c, is taken as 0.001.On clicking infer, the values in the respective textboxes are transferred to the appropriate cells in the initial state vector. For example, the value 0.9 representing pains in the eyes is transferred to A(1,1). Table 5 describes the other concepts.

Table 5: Table describing the position of each concept in the row vector

CELL	CONCEPT	CELL	CONCEPT
A(1,1)	Pains in the eyes	A(1,13)	Halos around light
A(1,2)	Red or pink eyes	A(1,14)	Poor night vision
A(1,3)	Conjunctivitis	A(1,15)	Cataract
A(1,4)	Burning eye sensation	A(1,16)	Cloudy lens
A(1,5)	Blurred vision improves with blinking	A(1,17)	Bright light improves vision
A(1,6)	Corneal Ulcer	A(1,18)	Astigmatism
A(1,7)	Swollen eyelid	A(1,19)	Family history
A(1,8)	Photophobia	A(1,20)	Eye bleeding
A(1,11)	Blurred vision	A(1,23)	Discomfort after long eye use
A(1,12)	Glaucoma		

Figure 5: Input user interface showing concepts that are activated

The adjacency matrix is described as Matrix B. Since majority of the interactions return a value of zero to the matrix (representing no relationship), we decide to initially declare an initial adjacency matrix consisting of zeros before updating those cells that have relationships. The initial adjacency matrix is declared using the MATLAB command: B = zeros (23).

IV. Results and Discussion

The sample cases as diagnosed using FCM is given in Table 6 this can be compared with the two opticians' diagnoses as presented in Table 3. Out of the 20 cases diagnosed by the two opticians independent of each other, the FCM diagnosis found 13 matches out of the 20 cases diagnosed by the first optician and 9 matches with that of the second optician. The study employs 20 datasets of patients with symptoms of eye

diseases. Out of this number, the first optician diagnosed the cases into 5 glaucoma cases, 3 conjunctivitis cases, 2 astigmatism cases, 3 uveitis cases, 2 cataract cases, and 5 corneal cases. The second optician diagnosed the cases into 4 glaucoma cases, 2 conjunctivitis cases, 2 astigmatism cases, 4 uveitis cases, 2 cataract cases, and 6 corneal cases. The FCM decision support system diagnosed into 4 glaucoma cases, 5 conjunctivitis cases, 1 astigmatism cases, 2 uveitis cases, 4 cataract cases, and 4 corneal cases. Thirteen (13) representing 65% of the diagnoses of the first optician matched with that of the FCM DSS, while only nine (9) representing 45% of the second optician diagnosis matched with that of the FCM DSS. False negative match for optician 1 is -0.21 while 0.24 is recorded for optician 2. The graph of the diagnosis correlation is depicted in Figure 6.

Table 6: Sample cases diagnosed using FCM

PATIENT NUMBER	EYE PAINS	RED/PINK EYE	BURNING EYE SENSATION	BLURRED VISION IMPROVES WITH BLINKING	SWOLLEN EYELID	PHOTOPHOBIA	WATERY DISCHARGE FROM EYE	BLURRED VISION	HALOS AROUND LIGHT	POOR NIGHT VISION	CLOUDY LENS	BRIGHT LIGHT IMPROVES VISION	FAMILY HISTORY	EYE BLEEDING	DECREASE IN FIELD OF VIEW	STEAMY CORNEA	DISCOMFORT AFTER LONG EYE USE	DIAGNOSIS	
1	0	.3	0	0	0	0	0	0	1	0	0	0	.5	0	1	0	.4	GLA 0.9	CAT 0.3
2	0	0	0	0	0	0	0	0	0	.6	0	0	.7	0	0	.8	0	AST 0.6	CAT 0.2
3	0	.7	0	0	0	0	.6	0	0	0	0	0	.5	0	0	0	0	CON 0.6	COR 0.2
4	.2	0	0	0	.7	0	0	0	0	.8	0	0	0	0	0	0	.9	UVE 0.4	CAT 0.2
5	.6	1	1	0	.2	0	.9	0	0	0	0	0	0	0	0	0	0	CON 0.9	COR 0.7
6	.1	.3	.4	0	0	0	0	.9	0	0	0	0	.4	.9	0	0	0	CAT 0.5	UVE 0.4
7	.9	.5	0	0	0	0	0	.4	0	0	.6	0	0	0	0	0	0	COR 0.7	CON 0.4
8	0	0	.4	0	0	.9	0	0	0	0	.9	0	.9	0	1	0	0	GLA 0.6	COR 0.4
9	.1	0	.2	0	0	0	0	0	.9	0	0	0	0	.7	0	0	0	GLA 0.4	CAT 0.3
10	0	0	.9	0	0	0	0	0	0	0	1	0	0	0	0	0	.6	COR 0.6	CAT 0.3
11	1	0	.9	0	0	0	0	1	0	0	1	0	.9	0	0	0	0	CON 0.9	CAT 0.7
12	0	0	0	0	0	0	0	.6	0	0	0	0	0	.9	0	0	0	CAT 0.4	UVE 0.1
13	.7	0	0	.1	0	.1	0	0	.1	0	0	0	.2	0	0	0	0	COR 0.3	UVE 0.1
14	0	0	0	0	0	0	0	.6	0	.9	0	0	0	0	0	0	0	CAT 0.5	UVE 0.1
15	0	0	0	0	.9	0	0	.6	0	.4	0	0	0	0	0	.6	0	CAT 0.4	AST 0.3
16	0	.8	.6	0	.9	0	.7	.6	0	0	0	0	0	0	0	0	0	CON 0.8	COR 0.5
17	0	0	.8	0	.9	0	0	0	0	0	0	.2	0	0	0	0	0	CON 0.3	COR 0.1
18	1	0	0	0	0	0	0	.8	0	0	.9	0	0	0	0	0	0	COR 0.8	CAT 0.6
19	.4	.8	0	1	0	.9	0	.4	0	0	0	0	0	0	0	0	.8	UVE 0.9	COR 0.5
20	0	0	0	0	.9	0	0	0	0	0	0	0	0	0	0	.9	0	AST 0.3	CON 0.01

CON = Conjunctivitis, COR = Corneal Ulcer, UVE = Uveitis, GLA = Glaucoma, CAT = Cataract, AST= Astigmatism

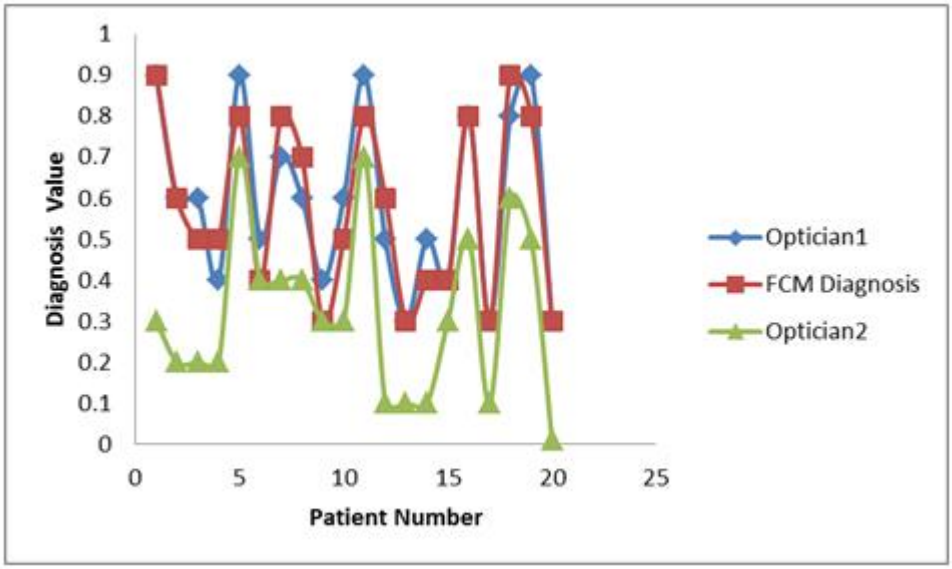


Figure 6: Graph of Diagnosis Correlation.

As shown in Figure 6, both optician 1 and FCM had diagnosis value of 0.9 for patient number 1 while optician 2 had a value of 0.3. Similarly for patient number 2, both optician 1 and FCM had diagnosis value of 0.6 while optician 2 had a diagnosis value of 0.2. FCM was observed to harmonize with optician 2 in the case of patient number 9 where both of them had diagnosis value of 0.3. However, in all cases of 20 patients, it was observed that the diagnosis values obtained from optician 1 and FCM were closer to each other than the values obtained from FCM and optician 2. The high correlation in diagnosis value between optician 1 and FCM could be attributed to accumulated experience of optician 1, acquired over many years of treatment of various kinds of eye diseases.

V. Conclusion

The design maps 17 symptoms of eye diseases to 6 eye diseases using weights assigned by 2 opticians. Training the maps in an unsupervised mode of Hebbian learning rule produced optimal weights that were employed to diagnose some cases of eye diseases. Results obtained were later compared to those diagnosed by 2 opticians and found to covary strongly with one and weakly with another. A novel feature of the differential diagnosis using the FCM methodology is the ability to give varying degrees of diagnosis of the main ailment and in addition that of an associated ailment. In doing so, the optician who is the ultimate user of the system could choose which of them to treat first maybe considering the severity of the ailment and how life threatening is one to another. Efforts are being intensified to gather large quantum of datasets to enable a case-based FCM development.

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