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Computational Model for Image Processing in the Minds of People with Visual Agnosia Using Fuzzy Cognitive Map

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Abstract

The Agnosia is a neurological condition that leads to an inability to name, recognize, and extract meaning from the visual, auditory, and sensory environment, despite the fact that the receptor organ is perfect. Visual agnosia is the most common type of this disorder. People with agnosia have trouble communicating between the mind and the brain. As a result, they cannot understand the images seen. In this paper, a model is proposed that is based on the visual pathway so that it first receives the visual stimulus and then, after understanding, the object is identified. In this paper, a model based on the visual pathway is proposed and using intelligent Fuzzy Cognitive Map will help improve image processing in the minds of these patients. First, the proposed model that is inspired by the visual perception pathway, is designed. Then, appropriate attributes that include the texture and color of the images are extracted and the concept of the seen image is perceived using Fuzzy Cognitive Mapping, the meaning recognition and the relationships between objects. This model reduces the difficulty of perceiving and recognizing objects in patients with visual agnosia. The results show that the proposed model, with 98.1% accuracy, shows better performance than other methods.

Keywords: Visual agnosia; Fuzzy Cognitive Mapping; Visual model; Mind.

1- Introduction

Agnosia refers to neurological conditions that results in an inability to know, name, recognize, and meaning extract from the visual, auditory, and sensory environment. This disorder causes the loss of ability to receive information through one of the senses, despite the fact that the receptor organ is perfect. [1, 2] Discrete brain lesions can lead to various forms of agnosia that may include any sense of error in individuals. There are several types of agnosia, including:

1-Auditory agnosia is the inability to recognize objects by sound (such as a phone ring). 2- Finger agnosia, which leads to impaired naming and recognition of the fingers of oneself and others and often follows damage to the parietal lobe. 3- Agnosia of a special category, in which people are not able to name living things but can say the names of objects (or vice versa). In this agnosia, the disorder in the right temporal lobe, which is specific to the perception of living things, and the left lobe for the perception of inanimate objects is the cause of this problem. 4- Semantic agnosia, in which people are so-called "blind object". They use the non-visual sensory system to recognize objects. For example, sensing, smelling an object is one of the things through which people can understand the meaning and concept of the object. 5- In color agnosia, people have difficulty recognizing and recognizing color but are able to understand and distinguish colors. 6- Alexei agnosia is the inability to recognize texts. 7- Tactile agnosia is related to the sense of touch, that is, the touch of objects. People have difficulty recognizing objects by touch based on their size, weight and texture. 8- In temporal agnosia, one has difficulty in understanding the sequence, duration and duration of events. 9- Music agnosia is a kind of agnosia in the field of music. This disorder causes a lack of recognition of musical notes, rhythm and intervals and an inability to understand music. Other forms of agnosia involve very specific and complex processes in one sense. It is questionable to describe why people can identify one type of object and fail to identify and define another. [1]

Visual agnosia is the most common type of this disorder. Visual agnosia or disorder in object recognition is a condition in which the patient is not able to recognize objects visually and pictorially. Although the role and

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function of the sense of sight is completely normal, means objects are observed, but the person is not able to percept their meaning, and cannot identify the object. [3]

In 1890, Heinrich Leicher argued that there were two conditions in which object recognition disorder could occur. They included if the damage would occur to the primary perceptual processing or if there would be a disorder in displaying the real object. If it was related to the display of the real object, it would not allow the object to be stored in visual memory, so the person would not be able to recognize the object. Leicher also proposed a visual recognition model that was presented at two distinct levels:

A. A perception, which expresses the function of perceptual processing of the stimulus (defect in perceptual processing).

B. Associative, which means perception with previous experiences.

Agnosia is caused by damage to the parietal lobe, temporal lobe, or occipital lobe of the brain. These areas store used and important memories of familiar objects, perspectives, sounds, and memory integration with perception and recognition. So, after damage to any of the lobes, symptoms will be revealed as follows:

● Parietal lobe: This type of damage is usually caused by a brain stroke. Indivisuals have trouble recognizing a familiar object (such as a key or pin). However, when they look at an object, they can recognize and identify it.

●The occipital lobe: In this injury, people cannot recognize objects such as a spoon or pencil even if they can see them. This disorder is called visual agnosia. They may not even recognize familiar faces.

●Temporal lobe: This damage can also cause auditory agnosia in which a person cannot hear sounds, as well as visual agnosia. [4, 5]

Diagnosis of agnosia requires careful examination of a person's mental state and cognitive abilities. In addition, the physician must carefully assess the individual's ability to perceive visual stimuli or other stimuli. In the case of visual agnosia, this process involves evaluating, measuring and testing a person's Field Of View(FOV), color perception, image, reading skill, face recognition, drawing and recognizing real objects and drawing lines. [6]

This disease could be diagnosed by brain imaging (such as Computed Tomography or Magnetic Resonance Imaging with or without angiographic protocol) or neurological and electroencephalographic tests, and treatment could be started as soon as possible. [6]

Andrea Serino et al. described the diagnosis of perceptual agnosia as a case report in their study. In perceptual agnosia, due to the nature of the injury factors, there will be primary visual impairment. Most injuries are due to lack of oxygen or carbon monoxide poisoning or heart attack, which often causes extensive neurological disorders. The report was about a patient with bilateral cortical injury in which the patient first suffered from cortical blindness and after improving, symptoms of perceptual agnosia were observed. The patient's low spatial intelligence prevented him from recognizing the unique attributes of visual stimuli. [7]

In a case study, Erickson et al. examined severe visual agnosia in a child with an electrophysiological pattern of output in the occipito-temporal regions. The child with sporadic seizure had an inability to recognize objects without visual impairment. After analyzing the maps, left occipito-temporal disorder was diagnosed and signs of perceptual agnosia were observed. [8, 9]

Barton et al. studied patients who had difficulty at object recognition (people with visual agnosia) and showed their differences from healthy individuals by considering the direction of their eye movement when looking at the image. Their interpretation was that eye movements could be modeled as a selection of highlighted points, indicating that agnosic individuals have an increasing reliance on visual highlighted parts such as brightness and contrast. In addition, it states that patients' different perceptual problems may be highlighted by selecting the weights of the various attributes involved in a map. Finally, they stated that highlights are not always a good predictor of agnosia diagnosis. [9]

Many computational models have been proposed to recognize mental structures. Moren and Balkenius presented a computational model for describing the structures of the brain that are involved in attention and perception. This model could help the mentally patients such as visual agnosia. The perception pathway of visual sensory inputs could be interpreted based on the structure of this model. [10-12] In the Moren and Balkenius model, a computational model of emotional learning in amygdala is introduced because the amygdala frequently intervenes in emotional reactions, learning and stimulators of new emotional symptoms, and forms an important part of the learning engine as well as attention. [13- 15]

The computational model of image perception is an engineering model that could be divided into three parts:

1-Primary Vision 2- Intermediate Vision and 3- High Level Vision. In the primary visual layer, a perception of the image regularities, including image texture, edge, slope, or symmetry, is performed. In intermediate vision layer, there are attempts at image analysis to divide the image into objects that are mostly namable. The output of the intermediate vision layer is a set of attributes that are extracted from the original image. These should contain data about the main structure of the body and be as constant as possible for different samples of a classification, as well as differing from each other for different classifications. [10, 11] In the high visual layer, the result of the previous stage is entered as a set of quantitative attributes that represent the object in a specific way. After reducing the amount of data about each object, while the main and important data is preserved, the correct classification of data is done. [13]

Recently, a class of computational models, termed deep convolutional neural networks (DCNNs), inspired by the hierarchical architectures of ventral visual streams demonstrated striking similarities with the cascade of processing stages in the human visual system. [16-18] Seijdel et al. Used Deep Convolutional Neural Networks as 'artificial animal models for detection of patient with object agnosia. They indicated that DCNNs with 'lesions' in higher order layers showed similar response patterns, with decreased relative performance for manmade scenes and natural. [19]

There is practically no direct treatment for patients with agnosia. Speech therapy or occupational therapy may help to compensate for the illness. In engineering sciences, an attempt has been made to take a step towards intelligent diagnosis and treatment of the disorder by mind modeling of these patients. The perceptual model attempts to provide individuals' perception in order to help patients with difficulty in perception based on these models. [11, 20, 21] According to the agnostic people have difficulty in understanding, a model based on it should be used. Previous research has not paid attention to perception in these people and very little computational model research has been done on agnosia, so here with a tool like FCM that works well in perception, this problem will be solved. So, using the advantages of Moren's computational model and combining it with vision perception pathway, would be solve the problem of image processing in these patients. In this model, Fuzzy Cognitive Mapping (FCM) is used for perception because in FCM, objects and processes are related to values and are modeling methods of complex systems whose origin corresponds to fuzzy logic and neural networks.

This paper is organized in such a way that after the introduction, in the second part, the materials and proposed method are presented. In the third part, the results will be analyzed and in the fourth part, conclusions will be expressed.

2- Materials and Method

The purpose of the present study is to improve the image processing in the minds of people with visual agnosia by the mind modeling using the modified Moren model and Fuzzy Cognitive Mapping (FCM). In fact, in this paper, according to the image perception pathway and considering the problematic part of agnosic individuals, the problem of not processing images properly in the brains and minds of these patients is addressed. In normal individuals, after observing an image, the image information in the visual pathway begins to rise from different regions of the visual cortex of the brain, and this phenomenon is what is known as direct data processing in the brain. Neuronal activities in the visual cortex of the brain begins to rise from the lower regions to the higher regions to reach the stage of image perception. Because patients with agnosia cannot recognize the objects' meaning and attributes, then, the current study uses FCM to compensate this deficiency for image perception in the proposed model.

First, the database images are selected and the appropriate attributes are extracted. Then, based on the model proposed, the read images are perceived and recognized. The proposed model is designed based on the vision pathway and image perception in normal people. So, after explaining the vision pathway and object recognition in normal people, the proposed model and its details will be discussed.

2-1- Object Recognition in Normal Individuals

In all individuals, there are 3 stages of information processing for object recognition:

Stage 1: Receiving visual stimulus; stage 2: object perception; stage 3: object recognition. [22] After receiving the stimulus, our thoughts visualize all the information, in other words, the information is displayed in the form of an image, and then people relate this image to what they knew in the past and perceive its meaning. Humans are able to recognize many objects around them without any problem, although these objects might be in different positions and with different viewing angles as well as different sizes. Even the human is able to recognize objects when he does not see parts of them or another object is in the pathway of his sight. Although this is very simple and practical for humans and mammals, it is in itself a very difficult and complex computational process. [23]

The cerebral cortex is made up of neural cells that make up the outer layer of the brain. It controls complicated activities such as memory, learning, problem solving, planning, sight, hearing, and movement. The cerebral cortex is divided into two hemispheres, each of which is divided into four areas: the temporal, the frontal, the parietal, and the occipital. The occipital part is located at the back and processes visual information.

The visual cortex is divided into different areas. V1 (Primary Visual Cortex) and V2 (Secondary Visual Cortex) are the largest areas and the area of each is about 1100 to 1200 mm. The information received from the retina is located through the LGN from the thalamus to the V1 in two separate pathways and is processed independently.

Object recognition pathway (ventral branch): The function of this pathway is to recognize the objects' attributes (color, shape, etc.) and it is located in pathways of V1, V2, V4, AIT and PIT. In the ventral stream, what is visualized is the output of what can be consciously seen and described. This stream creates a mental interpretation of the world around us. Color, relative size, texture and shape are all processed in this area. When people observe an object, a mental representation of that object is created, and this representation changes at least semi-permanently to what is referred to as memory. [23]

Object location Recognition Pathway (Dorsal Branch): The function of this pathway is to recognize the spatial characteristics of the scene (direction of movement, etc.) and it is located in the pathways of V1, V2, V3, MT and MST. Dorsal stream processes the visual input, so it is often referred to as the visual motor. Unlike the ventral, the dorsal stream does not form the permanent memories, but provides a continuous update of the recorded information for two seconds. [23] Figure (1) shows the different areas of the cerebral visual cortex.

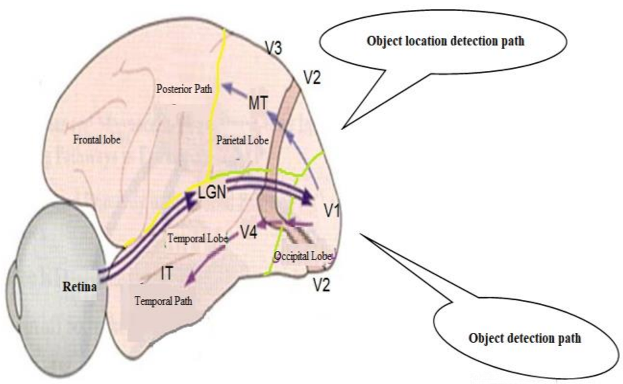

Fig. 1 Different areas of the cerebral visual cortex

The pathway of image perception in ordinary people contains several areas with extensive connections, each of which is responsible for processing part of the raw information collected by the eye. [24]

The Main Visual Pathways: In mapping the visual pathway, Mishkin stated that striate visual areas could be well separated not only anatomically but also functionally [25] including the Tectopulvinar pathway (system for visual motor control), the subcortical pathway including sc and pulv processes of some aspects of unconscious perception, and the Geniculostriate pathway (a system for visual perception). Figure (2) shows the cognitive structure of the visual pathways.

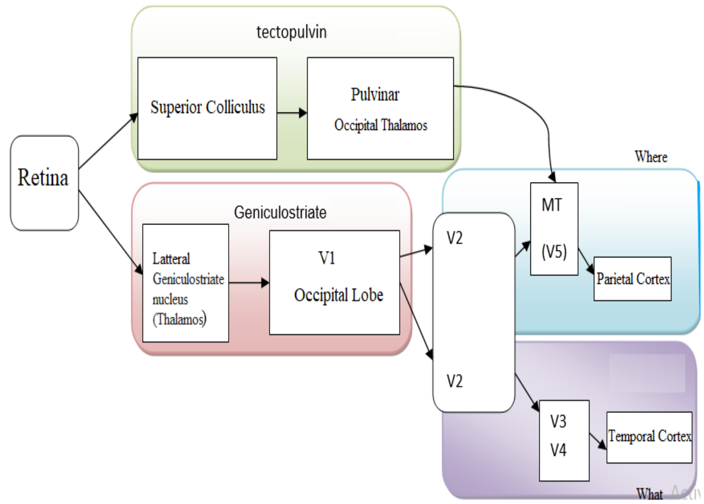

Fig. 2 The cognitive structure of the visual pathways

If the temporal lobe is damaged, these roles will also be impaired. Patients with right or left temporal lobe injuries have difficulty distinguishing and recognizing images, and even skills related to the formation of geometric shapes. Patients with right or left temporal lobe injuries have some difficulties reminding and recognizing objects and remembering their location. Visual information processing in the V4 region is integrated with stored memory patterns. Damage to this pathway can lead to visual agnosia. [25]

2-2- The Proposed Model

The proposed model has been designed based on the human visual model from observation to image perception. Due to the lack of perception of images in these patients, the perception problem in the present model has been solved with FCM. The structure of the proposed model is shown in Figure (3).

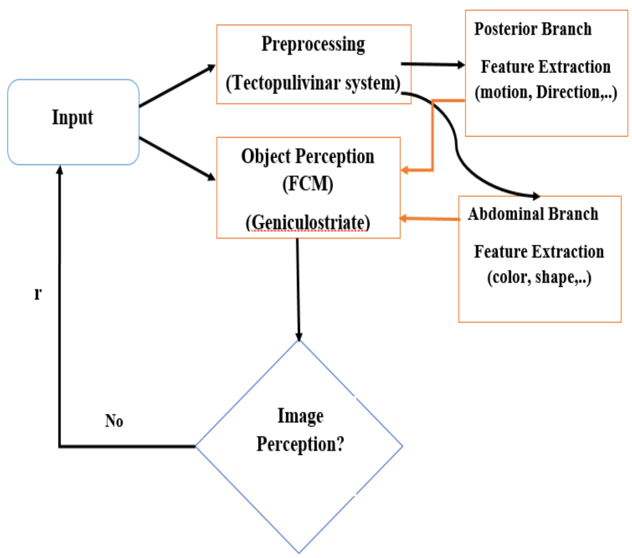

Fig. 3 The structure of the proposed model

As mentioned above, the proposed model, is based on the visual pathway from observing image to perception in the brain. The image is first read as input. The input image in the Tectopulvinar module will be pre-processed (noise cancellation, resolution improvement, etc.). In the posterior and abdominal branch modules, image features are extracted and entered into the Geniculostriate module for image perception. If the image is not perceived, the feedback r helps the system to be trained in perception again. Each of the components of the proposed model will be described below.

Feature Extraction: After selecting the images, the attributes have to be extracted. Here, those faetures with the most important role in separating image pattern classifications are extracted. The features used are described below.

Texture: GLCM are used to extract attribute from tissue. The features obtained in this way are contrast, entropy, energy and homogeneity.

A. Contrast: Contrast measures textures, using the following formula [26].

$$C = \sum_i \sum_j (i-j)^2 C(i,j) \tag{1}$$

B. Energy: Energy measures the textural uniformity of images and uses the following formula. [27]

$$E = \sum_i \sum_j C^2(i,j) \tag{2}$$

C. Entropy: Entropy measures the degree of irregularity using the following formula. [27]

$$H = \sum_i \sum_j C(i,j) \log\left(C(i,j)\right) \tag{3}$$

D. Homogeneity: Homogeneity measures the elements' distribution and uses the following formula.

$$HO = \sum_i \sum_j \frac{C(i,j)}{1+|i-j|} \tag{4}$$

Color torque**:** Color torques in which the recognition of color distribution in an image is measured in the same way as the unique central torques describe a probability distribution. Color torques are mainly used for color indexing purposes as attributes in image retrieval functions to compare the similarity of two images based on the color. [28]

A. Median: The median, which is the first color torque, could be interpreted as the average color in the image and calculated from the following equation.

$$E_i = \sum_{j=1}^{N} \frac{1}{N} Pij \tag{5}$$

Where N is the number of pixels in the image and Pij is the i-th pixel value of the image in the i-th color channel.

B. Standard deviation: The second color torque is the standard deviation, which is obtained by considering the second root of the color distribution variance.

$$\sigma_i = \sqrt{\left(\frac{1}{N}\sum_{j=1}^{N}\left(p_{ij}-E_i\right)^2\right)} \tag{6}$$

Where E_i is the median value, or the first color torque for the i-th color channel of the image.

C. Skewness: The third color torque is skewness. It measures how the color is distributed and then gives information about the shape of the color distribution. Skewness can be calculated from the following equation.

$$s_i = \sqrt[3]{\left(\frac{1}{N}\sum_{j=1}^{N}\left(p_{ij}-E_i\right)^3\right)} \tag{7}$$

D. Color indexing: The Color torque could be used to compare how two images are similar. This is a relatively new approach to color indexing. Color indexing is the main function of color torque. Images can be indexed and the index will include the calculation of color torque. Therefore, if you have an image and want to find similar images in the database, the color torques of the image in question are calculated. The following function will then be used to calculate the similarity score between the image in question and the database images. [29]

$$d_{mom}(H,I)=\sum_{i=1}^{r}\omega_{i1}\left|E_i^1-E_i^2\right| + \omega_{i2}\left|\sigma_i^1-\sigma_i^2\right|+\omega_{i3}\left|s_i^1-s_i^2\right| \quad (8)$$

Fuzzy Cognitive Mapping Design (FCM): FCM is a soft computational method for modeling systems and is extensively used for complex systems analysis and decision making. FCM is a directed graph to represent causal relationships between multiple concepts and has been widely applied in various fields to support decision making and task classification. Fuzzy cognitive mapping is a method of presenting efficient knowledge and reasoning that is based on human experience and knowledge and includes experts' opinions about a mental reality and requires data entry and training.

Useful attributes of FCMs such as simplicity, supporting inconsistent knowledge, the field of cause and effect relationship for modeling knowledge and conclusion, as well as learning capability, make them applicable to many different scientific fields of knowledge modeling, forecasting and decision making. In fact, FCM describes specific fields using nodes, concepts (variables, states, inputs, and outputs), causal relationships, and signed fuzzy relationships between them that could be positive or negative. Learning methods are used to train FCMs, which include updating the weights of causal relationships. Fuzzy Cognitive Mapping (FCM) is interpreted as follows. [26]

If FCM is the number of N nodes Ci, the value of each node in each iteration is computed as follows.

$$A_i^{t+1}=F\left(A_i^t+\sum_{j=1}^{n}A_j^t w_{ji}\right) \quad (9)$$

Where A_i^t is the value of the concept Ci at time t + 1, A_j^t the value of the concept Ci at time t, Wji corresponds to the fuzzy weight between the two nodes and F is the threshold function that converts the product to a number in the interval [0-1]. The function used in the present study is the logistic function given in the following equation.

$$F(x)=\frac{1}{1+e^{-\lambda\chi}} \quad (10)$$

Each node is a fuzzy set that could be excited from 0 to 100%. FCM connects objects and processes to values. The FCM modeling method is consistent with fuzzy logic and neural networks that grow in feedback. First an FCM is early valuated, then the activation level of each node takes a certain value of the system and different concepts are free in interaction. Activating one node affects the other nodes to which it is connected. This continues until the system reaches a constant equilibrium point or a finite cycle or a turbulent behavior. [30]

3- Discussion and Results

The test uses a 500 k Corel database that includes five classifications: Africa, beach, buildings, buses and dinosaurs. After calling the images, the features extracted from the images and the training is performed. In the test stage, the type and classification of the images will be recognized. To determine the efficiency of the proposed model, the criteria of accuracy, precision, recall and F1measure have been used. The following formulas show how to calculate them.

$$Accuracy=\frac{T_p+T_n}{T_p+F_p+F_n+T_n} \quad (11)$$

$$\mathrm{Pr}ecision=\frac{T_p}{T_p+F_p} \quad (12)$$

$$\mathrm{Re}call=\frac{T_p}{T_p+F_n} \quad (13)$$

$$F1\,Score=\frac{2\times\mathrm{Pr}ecision\times\mathrm{Re}call}{\mathrm{Pr}ecision+\mathrm{Re}call} \quad (14)$$

Where Fn is unrecalled related images, Tp recalled related images, Tn unrecalled unrelated images and Fp recalled unrelated images. Table (1) shows the comparison of the accuracy value of the proposed method with SVM and neural network methods in the number of different images.

Table 1: Comparing the accuracy of recognizing different types of images with the number of different images in the proposed model and other methods

Number of Images	***100***	***200***	***300***	***400***	***500***
Proposed Method (FCM)	82%	85.30%	86.90%	94.2%	98.1%
SVM	67%	69.4%	73.1%	86.3%	91.4%
Neural Network (MLP)	42%	58.2%	63.5%	78%	81.4%

As it could be seen, the proposed model performs better for more images, and with 98.1% accuracy has succeeded in recognizing objects while SVM, with 91.4% and neural network with 81.4% accuracy have recognized. Figure (5) shows the comparison of the performance of proposed model with other methods based on the accuracy, precision, recall and F1 measure.

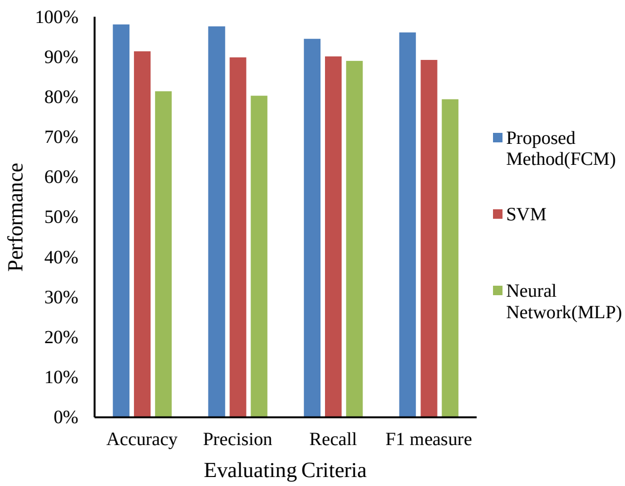

Fig.4. comparison of the performance of proposed model with other methods

As it is clear in the above diagram, the proposed method has performed better. Figure (6) shows the comparison of the performance of proposed model with the Moren mind, Balkenius model and CNNs.

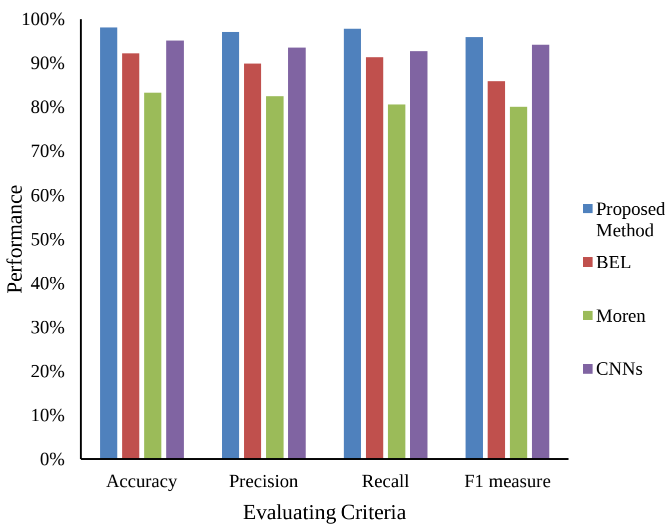

Fig.5: comparison of the performance of proposed model with other methods

As can be seen in the above diagram, the proposed model performed better than the other two methods. The accuracy of the proposed model was also compared with the Moren, Balkenius model and CNNs in different number of images and have been reported in Table (2).

Table 2: Comparing the accuracy of recognizing different types of images with the number of different images in the proposed model, BEL and Moren

Evaluation Criteria	***100***	***200***	***300***	***400***	***500***
Proposed Method	84.1%	87.30%	89.30%	94.6%	98.1%
BEL Model	65.1%	67.4%	76.2%	86.9%	92.2%
Moren Model	44.1%	59.2%	68.2%	780.1%	83.3%
CNNs	81.9%	82.6%	87.3%	92.1%	92.1%

As it could be seen, the proposed model has been able to have higher accuracy than other mind models due to the use of fuzzy logic.

4- Conclusions and Future Work

In this paper, a model was proposed to solve the problem of recognizing objects in patients with visual agnosia. In the proposed model, the human visual system was inspired by the structure of the visual cortex of the brain. In this model using FCM, intelligently helped to improve the perception of images in the minds of these patients. Perception was performed by recognizing the meaning and relationships between the objects in the seen image using extracting the features of contrast, energy, entropy, heterogeneity, color torque, median and standard deviation from the images. The proposed model reduced the difficulty of perceiving and recognizing objects in patients with visual agnosia. The accuracy criterion was compared in the proposed model with other models and it was revealed that the proposed model with 98.1% had a higher accuracy compared to SVM and neural network methods.
In the future, the accuracy of the proposed computational model can be improved with the help of new artificial

intelligence and image processing tools. For example, adding the capabilities of deep and convolutional neural networks to the current computational model can modify the performance of this model. In addition, other options can be added such as early diagnosing the disease using electroencephalography data. The proposed model is a simulation of a system that can help people with visual agnosia to understand and recognize images. In the second and practical phase of this model, a tool should be developed to help these people to identify the images.

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