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An Innovative Architecture to Model Human Brain as Cognitive Computation System

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ABSTRACT

This paper presents novel approach to model the human brain functionality as a cognitive computation system. Here the brain appears as two different levels: the sensor level (i.e., object level) and the concept level (i.e., ontological level). Each level has a different stimulation pattern. Concept level is dominant over the sensor level due to the hierarchal structure combining those levels. Using a new Perceptron model is important in achieving the intended goals that can be summarized in: a) Ability to preserve the input's importance. b) Ability to perform both temporal and spatial neuronal summation. c) Ability to dynamically change its structure by undergoing through rewiring condition when recognizing a new object. d) Ability for continuous learning and gaining experience with frequent practicing. The new architecture makes the brain seems as a cognitive system in which the basic unit of function (i.e. neurons) interoperability is best described using linear algebra principals. The system is examined by using the well known Iris Flowers dataset.

Keywords: Cognition, Experience, Learning, Neural Coding, Rewiring.

I. INTRODUCTION

During the last century, humans aspire to model the machine that mimics their abilities of thinking, learning and decision- making. These attempts are based on its basic understanding of the physiological functions. The development of the biological sciences together with the development of the imaging devices made the process of studying of human thinking sites easier [1, 2]. Artificial neural networks are considered as computational techniques that emulate how the human brain does its basic functions. The human brain is composed of an enormous number of nerve cells which are considered as the basic block unit of construction and function. Each of these cells are connected to many other nerve cells composing what is biologically known as neural networks and they create a very complex pattern of electrical signal transmission. The signals are transmitted among the neurons through special connecting areas called "synapses" [3]. Researchers started to study these biological facts and begun their attempts to model the basic nervous unit "neuron".

The first attempt to model a neuron was carried out in 1943 by McCulloch and Pitt who first proposed a computational neuron [4, 5]. Next, in 1958 Rosenblatt proposed the first neural network that is known as Perceptron [5, 6]. All the neural networks from their invention till now share common characteristics. They have the same building block unit "neuron" and the interconnection between these blocks units. The most commonly known neuron is the Perceptron modelled by McCulloch [4].

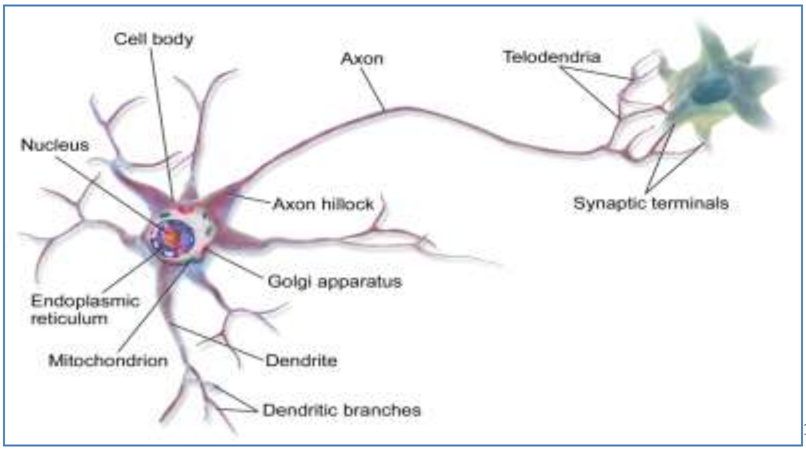
Since the basic idea was inspired from human biology and all the researches in neural network domain depend on the same block unit, the current studies show that there is a big demand to introduce some structural changes to the basic architecture of the Perceptron. The modifications should be done in a way that makes it converge more toward simulating the biological nerve cell. The following sections involve a brief introductive explanation about the subject of this article.

II. PERCEPTRON AND ARTIFICIAL NEURAL NETWORK

Before talking about Perceptron, we have to take an idea about the biological neuron. It is a special type of cells, composes the nervous system and the brain of humans and other developed species. Neurons have a remarkable property of electrical excitation [7, 8]. A typical neuron is divided into three main parts:

- Cell body "Soma".
- Dendrites.
- Axons.

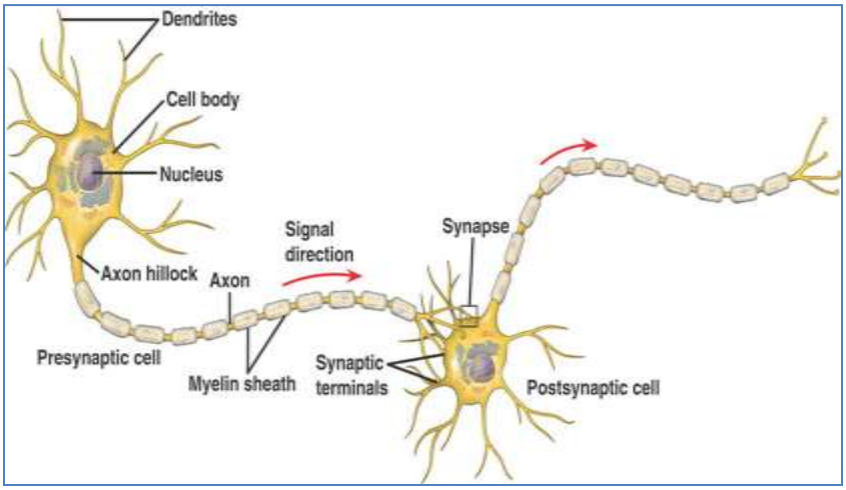
Starting with the Soma, it is the central part of the cell which is usually consolidate to biological function processing. Dendrites are small, branched filaments extrude from the cell body and become thinner as branching increases, they may extend distance away from the cell body. Axon is the long extension that also extrudes from the cell body “Fig.1”. The signal leaves the soma and extends to a long distance with a remarkable maintenance of soma’s diameter in away unlike dendrites’. Soma may initiate several dendrites but only one axon that can extend out of cell body [7]. There are three different types of neurons composing the individual’s nervous system. Sensory neurons carry the information from the sensory receptors up to the brain. Motor neurons are transmitting information from the brain down to the muscles and other functional organs. In addition to the previous two types of neurons there are the inter-neurons which are responsible for moving information among different kinds of neurons [9, 10]. What makes these cells different from other types of cells is their cell membrane that is created to be capable of sending and receiving electrical signals through their dendrites and axons. The process of electrical signals transmitting is carried out with the aid of a special kind of chemicals called neurotransmitters [7, 10].



[1]

Figure 1: Neuron component

The electrical impulses travel from one neuron to another through a special kind of structure called “synapses”. The synaptic signals are received from other neurons through the dendrites and sent by axons. The synapse is the contact area between the dendrites of one neuron and the axon of the other neuron [11]. Synaptic signal may be either excitatory or inhibitory. In general, if the net excitation of the neuron at a certain time is large enough, then the cell will generate an electric signal or pulse called action potential [12]. As shown in “Fig. 2” the pulse is originated at the cell body and is transmitted away through the long axon to contact other neuron. Recently, from the neuroscience studies, there is two kinds of summation that govern the net electrical excitation; “temporal summation and spacial summation”[13]. The presence of neuroscience studies focuses on the limitations associated with performance of the current model. Since the current model does not take these two types of neuronal summation into its consideration, in other words it is temporal in nature.



[2]

Figure 2: The transfer of electrical signal through the axon

[1]. The image in(Fig.1) is taken https://readtiger.com/img/wkp/en/Blausen_0657_MultipolarNeuron.png
[2]. The image in (Fig. 2) is taken from http://biomedicalengineering.yolasite.com/neurons.php

Artificial neurons as mentioned earlier are a computational technique that emulates the biological nerve cell. Perceptron represents the block unit of the artificial neural network. In fact, it is a linear classifier, and it is only able to solve problems that have to do with linearity [14].

"Fig. 3" shows the structure of the currently used model Perceptron. X_i, W_i and Y Represent the inputs, the weight and the output respectively. K is referred to some type of activation functions [15]. The mostly famous one is the sigmoid function. The neuronal firing is occurred when the amount of the weighted summation becomes larger than a given threshold. This is so far largely similar to the action potential generation. The recent studies ensure the presence of neural code that is carried through the action potential. The current Perceptron is not able to carry this code and is ignoring the importance of input's identity. It only generate a notification to trigger firing [3, 16].

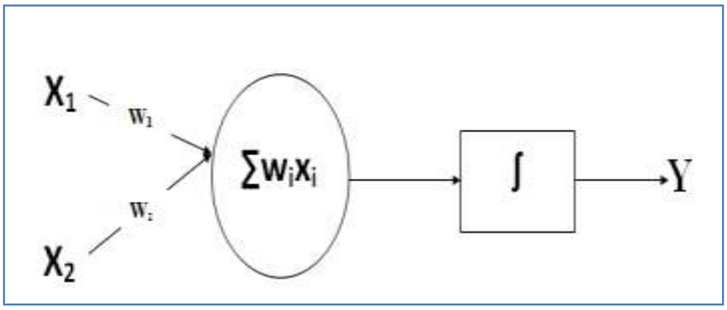


Figure 3: The Current neuron architecture

$$Y = K(\sum_i W_i X_i) \qquad (1)$$

The actual operative activity of the currently used model is depending on the training process. It possesses an amazing characteristic which is its ability to learn according to a certain training algorithm. Initially, feed forward algorithm was used in which the weights are adjusted through the training. As soon as the weights reach to satisfy the minimum error between the desired output and the actual one the training process stops and the Perceptron enters the operational mode [14, 17].

Actually, the effective success of the ability of the Perceptron is depending on the example patterns. The Perceptron is learning by example so that any new pattern that is not found within the training examples the Perceptron fails to identify it. This is because it depends on a certain computational steps to find out its results. Calculating the accumulative summation of the weighted inputs is the core process. This matter is conflicting with the human nature since the human thinking is depending on both cognition and computation [18, 19].

Upgrading from single layer Perceptron to multi layer Perceptron enhances the technique by adding number of hidden layers between the input and the output layer. It becomes able to solve more complex problems by using the same block unit but with different training algorithms. Learning algorithm diversity did not change the learning concepts "learning by examples". A new style of continuous learning will be used to learn and practice the proposed Perceptron [17].

All the applications involving the artificial neural networks share the same principles. The rigid, fixed structure is the distinctive feature of the current model [20]. The number of the hidden layers and the number of the nodes that is composing each layer in the network must be determined from the beginning; the nodes are fully connected to each other. This rigid structure isn't found in nature. In fact it is a conflict with the neuro-plastic nature of the brain [21-23].

Within the current development of the neuroscience, due to the appearance of new concepts like Neuroplasticity, rewiring, there is a real need to find a new neuronal architecture that really simulates nervous activity.

As mentioned previously, the neuron or generally the neural networks lack the ability to gain experience even after a long period of operational working. This is because the network is trained to learn but not to practice. Technically, there is a big difference between the two meanings, the studies show that there is a direct relationship between excessive practicing and gaining experience [18, 23]. Gaining experience shows a remarkable speed in performing actions and this is due to the increase in myelin sheath surrounded the nerve axons. The thicker is the myelinated axon the faster is transmitting the electrical impulses. The myelin will completely separate the axon and preserve the intensity and the direction of the impulse that is traveling through it from being lost [24]. This factor will be taken in consideration in this research since the proposed Perceptron design to involve a speed function that regulates its output selection according to its speed factor. The next section presents the mathematical model that answers the following questions:

- What mathematical concept can provide the capability of preserving the input importance?
- How to make the model able to perform both temporal and spatial summation?
- How to make the model have a dynamic, flexible structure and be able to change itself according to the external stimuli?

- Is it possible to design a model having a continuous learning properly?
- How to design mode that is able to gain experience on frequent use?

III. SUCCESS BRAIN MODEL CONSTRAINS

In order to achieve the neuronal functions in the scope of the new biological facts, the brain is working on two different levels. First, is the sensor level or it can be also called object level, during the sensory level human starts learning about objects through collecting the specifications and features of the objects from its surrounding environment. The object's feeling, sensation, other attributes, specifications and characteristics will represent the human neuronal inputs which are different from object to another. Each object has its own identity because it has its own neural code. On the other hand there is another level which is called the concept level, concept level is the storage area of the neuronal code; where each code represents a specific concept. These two levels have different stimulation patterns; concept level is the dominant over sensory level due to the hierarchal structure combining those levels. In this proposal the brain is presented as a cognitive computation system in which the internal kernels (i.e., neurons) interoperability is best described using linear algebra principals. Through investigating multiple resources about the internal mechanism of the brain, the suggestion is that, in order to get a successful brain simulation the following constrains are needed to be fulfilled.

Let:

neo_i^o : be a neuron from the sensory level (i.e., object level).

neo_j^c : be a neuron from the concept level.

S = $\{S_1, S_2, \dots, S_k\}$ is a set of stimulations in the sensory level

1- Stimulation : internal + external

2- Brain is re-arrange itself whenever a stimulus arrives (i.e., connections are established all the time in the learning process others are weakening).

$$\exists_{s \in S} \exists_{neo_i^o} \exists_{neo_j^c} \; fired(neo_i^o, s) \wedge Stimulate\left(neo_j^c \right) \rightarrow Bind\left(neo_i^o, neo_j^c \right) \tag{2}$$

3- Neuron activation, in the concept level, is represented by train of APs (Action Potential) pulses that code the stimulation pattern (i.e., neurocode).

$$\exists_{s \in S} \exists_{v} \exists_{neo_j^c} \; mapping(v, s) \; \wedge fired\left(neo_j^c, s\right) \rightarrow \; assign\left(neo_j^c, v\right) \tag{3}$$

$$\exists_{s \in S} \exists_{v} \exists_{neo_j^c} \; mapping(v, s) \wedge fired\left(neo_j^c, s\right) \rightarrow \; assign\left(neo_j^c, v\right) \tag{4}$$

$$\forall_{neo_j^c} \; assign\left(neo_j^c, v\right) \rightarrow \; \theta(j) \tag{5}$$

4- Not all post-synapses respond in the same way to the incoming APs

$$\forall_{i,j} \; Projection(\; \theta(i), \theta(j), (out)x\text{: } integer) \wedge (x \; \geq threshold) \rightarrow Stimulate(j) \tag{6}$$

5- Axons promote their performance in transferring APs to the synapses and later to the post-synapse of the next neurons:

$$\forall_{i,j} stimulate(j) \rightarrow IncreaseSpeed\;(j) \tag{7}$$

IV. PROPOSED MODEL ARCHITECTURE

In the proposed architecture, the neurons' action potentials (APs) are transmitted in structures which represent the stimuli patterns. The information is coded within firing rate. The response of connected neuron through their synapses is highly proportional to the nature of these structures. In this proposal, the activation of a neuron generates output that holds the input signature via its direction. Hence, the stimulation pattern is transferred over the neural net as shown in "Fig. 4", [25, 26].

$$\vec{v_i}\,[SOD] = \vec{u_i}$$

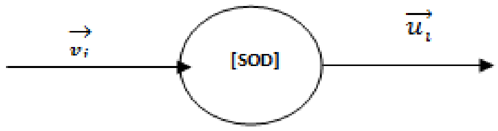


Figure 4: The proposed neuron

The neurophysiologic summation or what is known as frequency summation whether it is spatial or temporal is the process that determines the occurrence of action potential at the post-synaptic neuron (recall sec.1). The difference between them is that in case of temporal summation, a single input can drive the neuron into activation based on the intensity of that input. Then the postsynaptic neuron receives repeated input from a single presynaptic neuron and the frequency with the strongest intensity. When the intensity is able to pass a voltage threshold then it can trigger an action potential. This is what is really happened in the current model. "Fig. 5"shows the temporal nature of the current model in which the activation level is the absolute summation of the individual intensities.

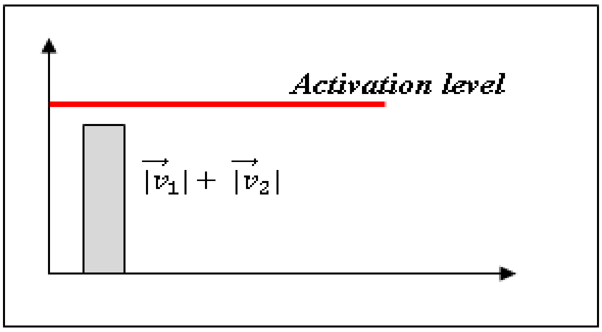


Figure 5: Temporal summation of the current model

Here a question may arise; what about the spatial summation; when the neuron receives multiple simultaneous input frequencies?

Keeping in mind that each input has its own identity and intensity so that for different stimuli each with different identities and intensities [27]. For example each pain has its own signature; current model fails to preserve the input identity. In this article there is a suggestion to use the inputs as vector in space instead of scalars. Each vector has its specific features that describe the stimulation type. Vectors are good representation since it is easy to preserve its identity by preserving its direction angle [28, 29].

Since the neuronal stimuli are summed biologically according to two kinds of summations; temporal or spacial [16]. The spacial summation is due to receiving stimuli from different sources, each has its own characteristic. Frequencies cannot be summed as simple scalar quantities [30]. Therefore the idea is to get benefit of linear algebra concepts and vector mathematics to provide a method for representing and preserving the stimulus identity. Accordingly, this study suggests using vector in space as representation of inputs instead of scalars to emulate the neuronal stimulus. Since the vector has both intensity and angle, vector intensity is used to trigger the neuron temporally to produce firing as in case of triggering the current model while vector's angle is used to represent the vector identity spatially since it has constant orientation [31, 32]. "Fig. 6" presents the method to represent spatial summation in the proposed model. Although the input's identity preservation is considered as a novel modification in the Perceptron's architecture, the scheme shown in "Fig 4" still lacks one of the most important features in human brain which is the experience [33]. Experience is acquired from internal and external resources through practical engagement, theoretical engagement and theorem proving [34]. Repetition of a certain habit is the magical word in gaining perfect experience [23]. A special layer (i.e., sheath plates) is built around the axon to maintain transferred signal[35]. The speed of signal transfer is increase dramatically[36]. "Fig.7" considers the mentioned facts and aggregates them to build the complete model for the neuron.

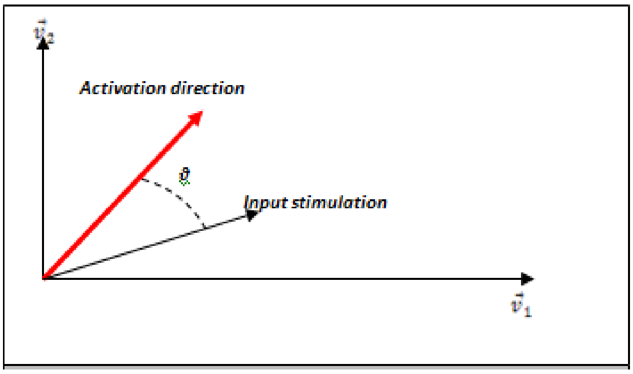


Figure 6: Spatial summation of the proposed model

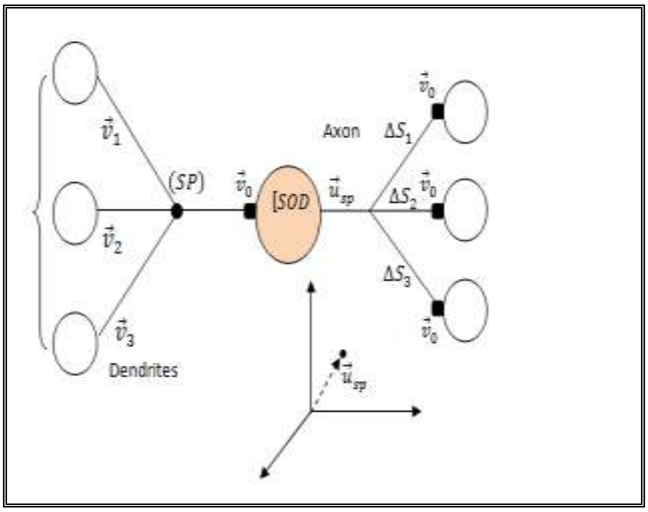


Figure 7: The complete proposed neuron architecture.

V. THE IMPLEMENTATION SEQUENCES OF THE TWO LEVEL SYSTEM

This section describes the architectural model of the proposed system using the same mathematical model published in our previous article [26]. The biological facts that are discussed in details in section one point to unique idea; "that is the human collects the information from the surrounding environment which has a big role in the development of their sensory system, then the excessive learning and acquisition lead to what is widely known as experience". Taking these facts into consideration this assumption has been built. The proposed model supposes that individual's cognitive system is composed of two levels; the first is called the sensory level and the second one is called the conceptual level. The next two sections illustrate the detail description of these two levels.

A. *Sensory Level Implementation*

The objects in our environment have a certain specifications; these specifications will mathematically represent the input vector coordinates. [SOD] matrix is used to preserve both vector direction and vector magnitude [26]. It is very trivial to calculate the output vector norm which is used later on as input to the sigmoid transfer function of the proposed Perceptron. Passing a certain threshold is important to trigger the neuron and cause firing. The novelty of the proposed Perceptron here as said earlier is by calculating the direction of the input vector (theta angle) which represents the vector's orientation in the space. The orientation of the input vector represents the input identity or its signature the subject that this study is concern with, and looking for a mean to preserve it.
As soon as the theta angle is calculated, the system will direct the concept level to prepare neuron for storing the theta angle as a new concept. The angle points to the most effective specification that makes the object more distinguishable among its environment.
Vector in space is the most convenient way for simulating the fact "human is a pattern seeker", since the brain has the capability of acquiring the ubiquitous information from the environment and incorporate these information into the brain to build more and more neuronal connection as the process of practicing is continued which is leading to gaining experience. More information means more synaptic connection, as the process repeated the synaptic connections will be thicker otherwise the connection will be trimmed.
Other novelty of using vectors as input and calculating the angle of orientation is simulating the spacial frequency summation which was illustrated previously, since the information received from different sources each with different

intensity and characteristics so there is one inevitable solution to do frequency summation rather than ordinary temporal (scalar) summation.

B. *Concept Level Implementation*

The proposed system is an attempt to simulate brain. The brain is capable to develop and reorganize itself using its neuroplastic ability [9, 37]. “Brain Neuroplasticity” is divided into two categories; the first one is “experience expectant” simulated by the sensory level that has been explained in the previous section (see sensory level) which is totally concerning with collecting information from the surrounded environment. Actually, it is designed to sort information that is underline to many sensitive and critical phenomena like contrast bordered and so on.
Human and other mammalians supported with an evolved nervous system. The evolved neuronal mechanism gets benefit from the environment that provides all species with the experience and provides a storage area to store them in the form of electric code passing through a certain path that is paved for it. This storage area is called “experience dependent”, concept level is designed to simulate this storage area for the learned objects to remember them later on. Once the Perceptron within the sensory level has fired and the theta angle of the input object calculation starts, the system will be directed to store the angle in the concept level space. The angle is an indication to the object’s pattern to distinguish it if it comes once again.
When the object appears again in the surroundings, the system will check whether its concept level has stored this object previously or not. This is done by taking the projection of the newly seen object and the already stored one. Measuring the degree of similarity between the two objects is the judge in the recognition process. If the degree of similarity represented by the angle of rapprochement between the two objects is within a certain threshold as in this case doesn’t pass 10 degrees so the two objects are similar otherwise the system undergoes through a condition known as rewiring.

VI. RESULTS

The results obtained from different stages during the process of implementing and testing the proposed model will be illustrated in this section. The proposed system and its basic Perceptron are examined using Iris Flowers dataset. The data set consists of 50 samples from each of three species of *Iris* (*Iris setosa*, *Iris virginica* and *Iris versicolor).* Four features were measured from each sample: the length and the width of the sepals and petals.

Only one Perceptron is used to differentiate the three species of the Iris flowers. “Fig. 8” shows the Perceptron used to recognize the three species of Iris Flowers. Without any previous training, the proposed model calculates the direction angle of the first incoming vector (object) that represents the first Iris type (*her is the Iris setosa*). The neuron will register it as a first concept. Then the system starts to compare the direction of the next incoming vectors (objects). It’s a relative similarity process, if the first object is closely related to the next incoming one within a predefined range of angles (*three to five degrees in our case*) then they are the same types otherwise the model starts to build a new connection. This process points to existence of a new different Iris flower type. “Fig. 9” shows the capability of the proposed model to discriminate the three types of flowers. Notice that the Perceptron receives new data without previous knowledge about it. This is considered as indication to the ability of the proposed model to recognize unfamiliar patterns.

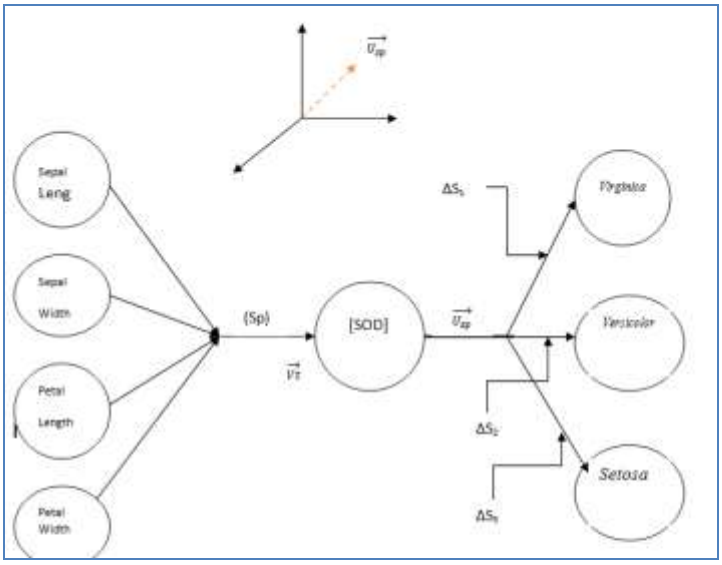


Figure 8: The proposed model for Iris Flowers recognition.

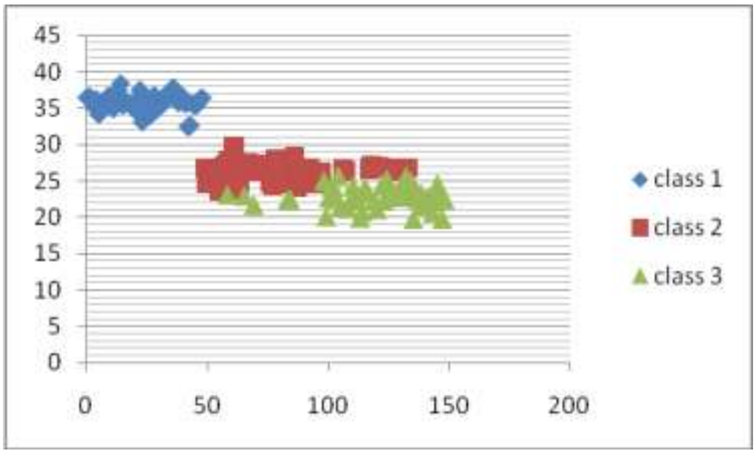


Figure 9: Iris Flowers discrimination.

A. *The Main New Features*

Many important features were added to the artificial neuron via using the proposed model [26]. The features have their novel characteristic effect on the results at all. These effects will be listed in the following point:

1) ***Keeping on object direction preservation***

This feature is verified by getting the benefit of the dyad matrix instead of accumulative summation used in the current architecture as it is well known. The opinion based here on the disability of the current model to take in consideration the neuronal input importance, it can't determine the identity of its input.

Secondly its successfulness depends on the learning patterns that determine the weights. The main reason behind the disability is the accumulative summation. However human doesn't use this kind of calculation during the process of cognition especially in case of linearity. Passing a certain threshold is important to cause neuronal firing (input vector norm).The neuronal firing lead to determining the input vector direction. The direction represents the identity of the input.

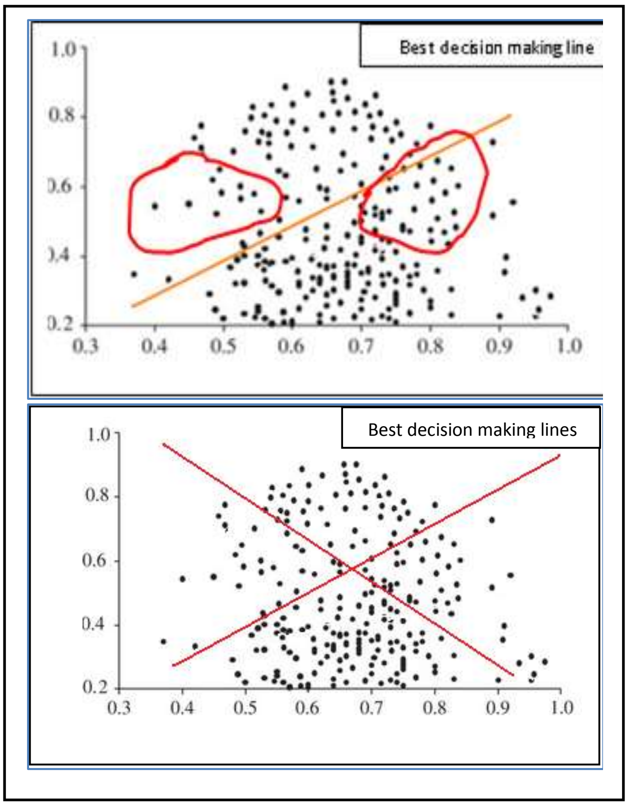


Figure 10: The difference in separation ability between the two models.

"Fig. 10" shows the difference in the separation ability between the two models. The amazing ability to discriminate objects is due to the use of dyad matrix. The effect of the special transformation matrix was previously explained in [26].

2) ***Code Transmission Rather than Notification***

As mentioned previously during the literature survey through the neuroscience publications, the biological fact said that the transmission across the neurocortical synapses depend on the frequencies of the presynaptic activity. The activation is a pronounced frequency dependent of synaptic responses to a train of presynaptic spikes. Recalling the activation of the currently used Perceptron depends totally on thresholding. Passing a given threshold will cause neuronal firing, the firing doesn't carry any semantic information it it's only a notification. However this is opposing the biological facts, therefore there is a serious need to invent a new architecture with a good ability to carry and store the neuronal code to be used in the future.

The proposed model follows a new style of activation in which the firing depends on the direction of the stimulus represented by the stimulus vector's angle stored in the concept level in addition to thresholding. Here the stimulus vector has a pattern or identity the direction of the vector composes this identity, it is largely simulate the brain's neuronal code.

3) ***Dynamic Structuring (Rewiring)***

Rewiring is the most convenient word that gives the exact meaning of brain reorganizing capability or the previously mentioned concept "Brain Neuroplasticity".

Recalling the currently used model, the number of layers and the neurons that constitute these layers will be determined at the beginning in accordance to the intended purpose for which the neural network is prepared. However biologically, the group of active neurons will be dynamically changed according to the incoming stimuli. From this point of view the current model lacks the ability to change its structure because of its stiff architecture.

Concerning the novel architecture of the proposed model, the adoption of the vectors in space concept as a mean to maintain the stimulus pattern that lead to the registration of that stimulus as a neurocode within the concept level. This facility gives the model an innovative dynamic ability to re-change the network structure in accordance to the intended purpose. The new Perceptron architecture shows a good dynamic structure. In addition to its excellent tendency toward extending a new connection as an evidence of recognizing a new object. There is direct relationship between the convergence angle and the experience rate. As the convergence angle decreases and converges to zero the experience rate shows its highest level and vice versa "Fig. 11 ".

The frequent firing lead to increase the experience rate of that branch in a way closely similar strengthens the human dendrites of that branch.

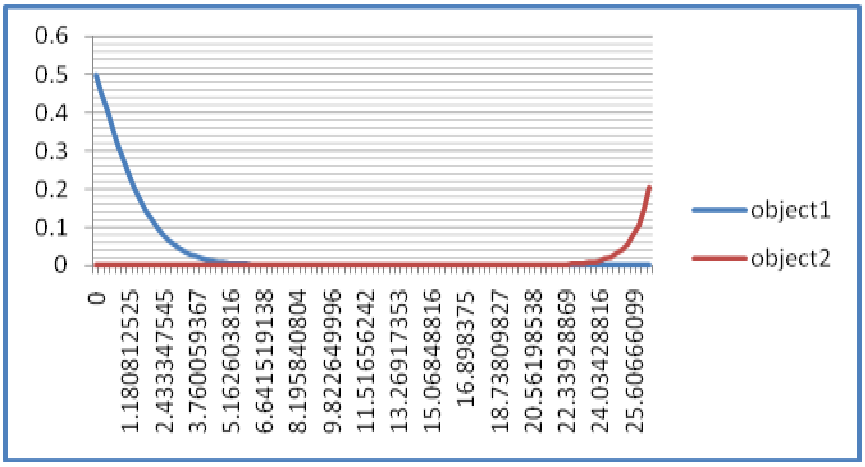


Figure 11: The behavior of the proposed model toward object's discrimination.

"Fig. 11" shows the relationship between the experience rate and the convergence angle where the x-axis represents the convergence angle while the y-axis represents the experience rate.

As it is shown "Fig. 11" the model is able to discriminate between two visual objects based on convergence of the vector which represents the visible object toward the stored one. The experience is increased when the visual object confirmed by the logical unit in the brain. Therefore the experience will be increased accordingly and the object recognition will be equal to the convergence angle plus dynamically change speed rate.

4) ***Experience due to Speed Parameter Changes***

Another novel feature involved within the proposed model is the invention of a parameter called "Speed Factor" or "The Gain Factor".

This concept is representing the brightening characteristic that differentiates this model from its precedent. The speed at each post synaptic junction is analogue to the well known mathematical concept singular valued decomposition (SVD). The speed at the vector direction is responsible for binding the concept domain to the object domain. Each successful firing will lead to the excitation of a certain branch. This excitation will change the speed factor and increases the gain toward retrieving the concept level's neuron attached to that branch "Fig. 13 ".

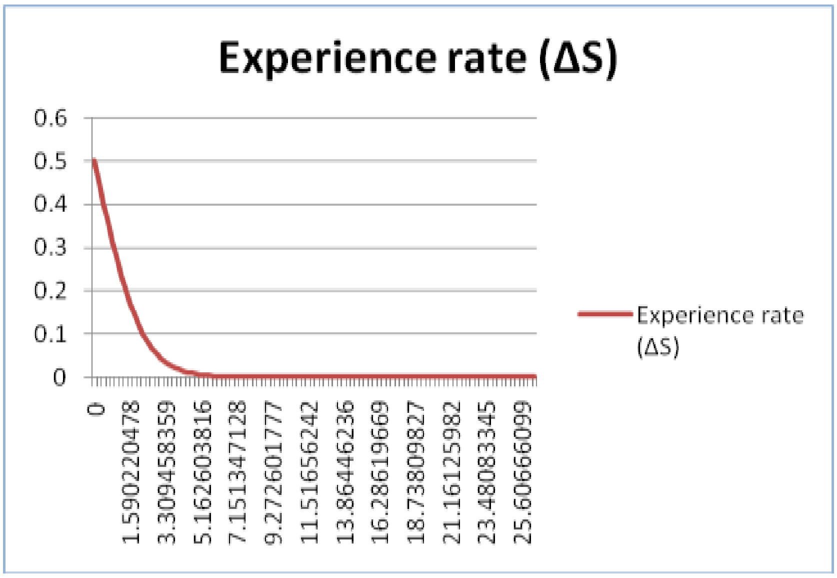


Figure 12: The experience rate change dramatically with firing.

Repetition of successful firing means identification of the same object via passing through the same path (branch). Frequent selecting the same conceptual neuron is analogy to increasing the axon thickness, and as a result leading to incremental speed in the diagnosis. "Fig.10" is an indication points to the appearance of new feature which is gaining experience of frequent use.

There is a big difference between learning and practicing. Practicing can give an expert while learning not. Learning courses don't create an experts person, and human may need several years to be a professional in a certain domain. A new style of learning will be discussed during the next section. Although the object features play an important role in the recognition process, the intensive practicing will improve the diagnosis in case highly similar objects. The higher speed is the candidate for activation due to the input events and the speed is the experience gained along the runtime of the proposed model "Fig.11"

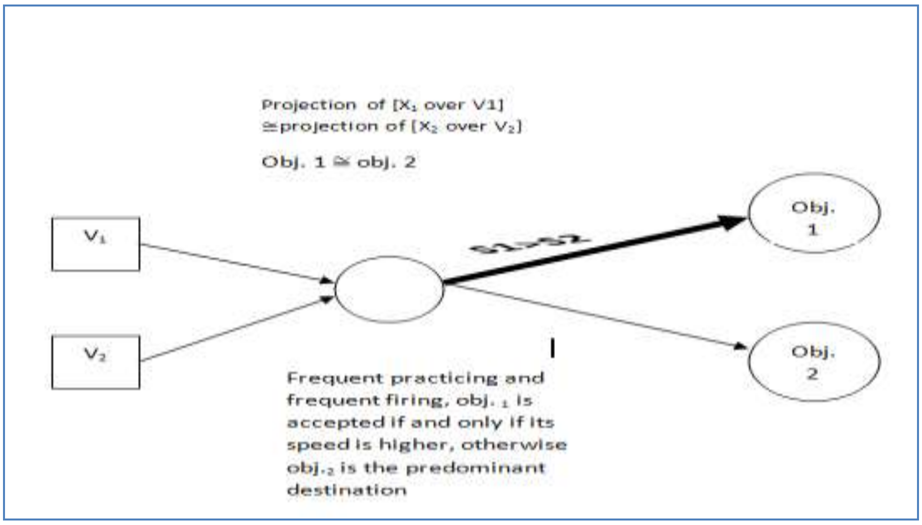


Figure 13: The effect of speed factor on final decision.

B. *Evaluation Metrics*

This section presents some evaluation metrics like sensitivity of the algorithm, specificity and accuracy depending on information extracted from confusion matrix. The confusion table is constructed to show the truly predicted cases that appear on the diagonal line of the table (Table. 1). In addition the cases that the system fails to recognize them correctly are found in other places of the table. A confusion matrix is constructed to exhibit the number of true cases as well as the number of false cases "Tables. 2". The true cases are subdivided further into two classes showing the ability of the algorithm to classify the positive cases as true positive (TP), and the negative cases as true negative (TN). Respectively, similarly, the false cases are also subdivided into false positive indicating the false cases which are predicted as true (FP), and the false negative which pointed to the positive cases that are negatively classified as false (FN). (Table. 1) shows the cases of the data set. The diagonal represents the positively diagnosed cases.

	Predicted Results			
Actual Results		Class1	Class 2	Class 3
	Class 1	50	0	0
	Class 2	0	47	3
	Class 3	0	7	43

Table 1: Table of confusion

	Predicted Results		
Actual Results		True	False
	True	True positive (47)	False positive (7)
	False	False negative (3)	True negative (93)

Table 2: Confusion Matrix

"Table 2" shows the confusion matrix of the system under question. The dataset of the system as mentioned above composed of 150 items of three different species. It is very clear that class 1(iris setosa) can be easily separated from both other classes. While class 2 (iris versicolor) and class 3 (iris virginica) are seemed to be as one cluster. By applying the proposed model using only one Perceptron that received the four features required to distinguish among the three species together. The results in the table will be used to calculate the biometric calculations.

C. *Algorithmic Metrics using Confusion Matrix*

Many evaluation metrics are available for evaluating the performance of a certain model. Sensitivity, specificity, accuracy, precision, recall, and F1 score are examples. In the following section three parameters will be calculated which are respectively, sensitivity, specificity and accuracy for two threshold angles 23.5° and 24°. The two angles reflect the accumulation of the true instances for both class 2 and class 3 around them, since class 1 is totally separable.

1) *Threshold angle at 23.5°*

- **Sensitivity** (also called the **true positive rate**) measures the proportion of positives that are correctly identified.

$$sensitivity\ TPR = \frac{TP}{TP+FN} = \frac{47}{50} = 0.94 = 94\% \qquad (8)$$

- **Specificity** (also called the **true negative rate**) measures the proportion of negatives that are correctly identified.

$$specificity = \frac{TN}{TN+FP} = \frac{93}{93+7} = 0.93 = 93\% \quad (9)$$

- **Accuracy:** this parameter is not always reliable metric, sometimes it yields misleading results specially when the dataset is unbalanced (when one of the dataset classes is much larger than the other classes but in our case the dataset is balanced 50 species of each type composing 150 items

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{P+N}} = \frac{47+93}{54+96} = \frac{140}{150} = 93\% \quad (10)$$

2) ***Threshold angle 24°***

$$sensitivity\ TPR = \frac{TP}{TP+FN} = \frac{43}{43+7} = 0.86 = 86\% \quad (11)$$

$$specificity = \frac{TN}{TN+FP} = \frac{81}{81+19} = 0.81 = 81\% \quad (12)$$

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{P+N}} = \frac{43+81}{62+88} = \frac{124}{150} = 82.6\% \quad (13)$$

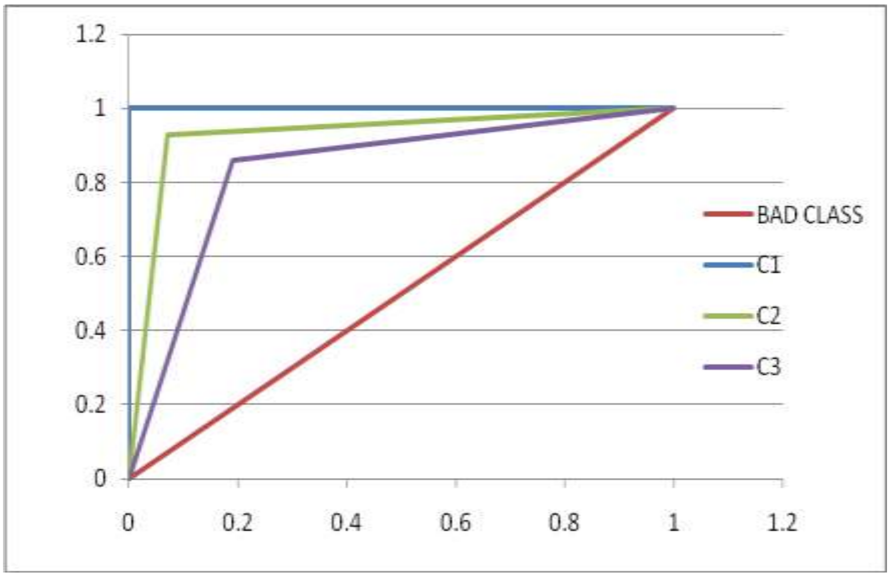


Figure 14: ROC curve of the proposed model

"Fig. 14" shows the recievor operating characteristicurve (ROC) is a graph that illustrates the performance of a certain binary classifier system. The true positive rate (sensitivity) as a function of false positive rate(100- specificity)."Fig. 15" represent ROC curve for the same dataset using the current model. During the comparison made between the two curves, the current model shows better performance than the proposed model.

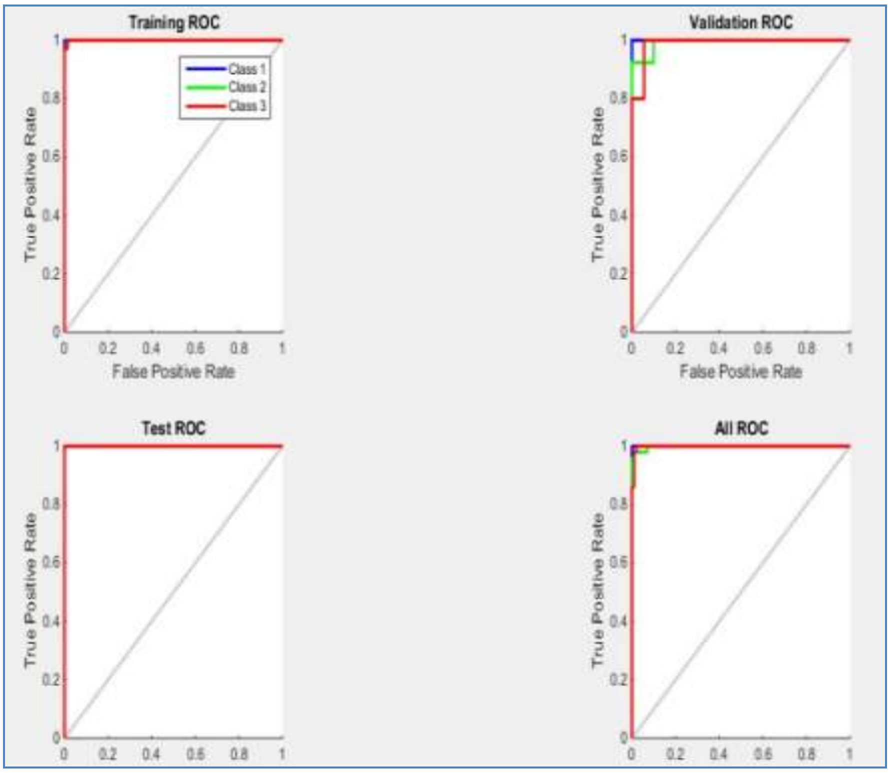


Figure 15: ROC curve of the current model.

Although the currently used model gives an excellent diagnostic results, but its results always on behalf of the network complexity that lead to increasing the execution time. Keeping in mind that only "one perception capable to give about 93% accuracy". This reduction in network architecture will open the door for getting promising results for many complex and sophisticated problems.

VII. CONCLUSION AND FUTURE WORK

The model was suggested to simulate human brain using a new Perceptron architecture, the new architecture designed to achieve four important features, these features where absent in the current model, these feature can be listed as follows:

- Preserving the stimulus input pattern, where the stimulus pattern mimics the neural code, so the Perceptron has the ability to transfer code in addition to the notification.
- Creating a flexible topology through the capability of rewiring.
- Gaining experience via introducing the speed factor.
- Continuous learning style based on measuring the relative similarity to the already known objects.

The efficiency of the proposed Perceptron to achieve the above goals was examined, by testing the ability to discriminate the three different classes of "IRIS FLOWERS" dataset. The Perceptron discriminate the objects without previous knowledge about them.

The fitting of the correct cases around the angle (23.5°) shows sensitivity toward the true cases that identified true equal to (94%), and specificity toward the false cases that are identified false to (93%). Concerning the algorithmic complexity, both testing has been done using only one Perceptron, therefore the new model shows significant decrease in the computation time and space because of absence of the huge amount of computation needed for multilayer network, keeping in mind that the process of separating the three class of the Iris Flowers needed at least (5), hidden neurons to get approximate results.

The new architecture gives the model the strength to achieve the following goals:

- Stimulus pattern preservation, achieving this goal is very important since it is considered the solid concrete that gives the potential to the transformation from computation to cognition; using vectors in space together with SOD matrix are responsible for achieving this goal.

- The model has a dynamic property to rewire itself and initiates a new connections as sign of finding new objects, this is considered an indication about the capability of the new model to form dynamic structure closely simulate the neuroplastic prosperity of brain. The success in achieving dynamic structure property plays the important role in reaching the concepts of continuous relative learning and experience.

- Continuous relative, learning about new objects and opting out of the examples exist in the training sets are another goal was achieved in this research. This property is considered as cornerstone in the process of recognizing the unfamiliar patterns. The challenge the world is facing now days especially the Middle East region after the appearance of strange medical diseases as results of war disasters and using different kinds of weapons.

- Rapidly running toward the already known object as an indication of gaining experience toward the well known objects. The higher speed is the most candidates for activation due to the input events and the speed is the experience gained along the runtime of the proposed model.

In general a brief summarized comparison between the currently used model and the proposed one is shown in "Table. 3".

Feature	Traditional	Proposed
Preserve Stimulus pattern	No	Yes
Based on input event topology	No (scalar)	Yes (spatial)
Network Interconnection	Fixed	Dynamic
Action potential coding preservation	No	Yes
Ambiguity	possible	Rare
Contradiction	Possible	Rare
Physical implementation	Yes	Yes
Inter-processing calculation methodology	Probabilistic	Stochastic
Learning style	fixed	Continuous

Table 3: Summarized comparison between the two models.

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