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Modular Neural Networks Chronicles in Biological Aspects

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ABSTRACT

Modular Neural Network Is A One of The Model Of Artificial Neural Networks. This Manuscript Describes The Urge Of Modular Neural Network (MNN) And How It Can Be Applied In The Biological Aspects, Since All The Cell Functions Are Modular In Nature And Can Be Applied In All Most All Cell Structures And Function Through The Connectionist Approach And The Weightless Logical Approach For Best Optimized Error.

Keywords : *Modular Neural Network, Architechture, Evolutionary Approach, Connectionist Approach, Weightless Logical Approach.*

I. INTRODUCTION

As an artificial neural network is an information-processing system that performs convinced features on biological neural networks. Mathematical models of cell functions can be accomplished by one of the model of ANN i.e Modular neural networks. Modular neural networking is the learning of networks of flexible nodes interacting with other nodes /neurons which are developed for generalization of neural biology.

Our human body contains near about 100 trillion cells, as cell is the basic structural, functional and biological units with the help of this cell n number of system runs in our body that is digestive system, endocrine system, immune system lymphatic system nervous system muscular system reproductive system skeletal system respiratory system urinary system integument system all this above system are computerized based on the concept modularity.

II. METHODS AND MATERIAL

A. Modularity

Modularity is motivated by human body processes, which involves a combination of serial and parallel processing. Neuropsychologists study revealed that the information processing system of humans is focused particularly on a partly damaged brain. The damage region of the brain has stopped implications on the cognitive abilities which are situated in this particular area. The non-damaged parts are still working and its performance is improved to compensate the loss in the other parts. These results that the brain has a highly modular and parallel structure

Modularity concept in the brain functioning results in optimization of the information capacity in the brain neural pathways. Since the brain consists of many modules and some f the modules are repeating using the feature of replication.

Modularity is the building block of Modular neural network, this network is based on reverse engineering[2,3,4,5,6] Classification[7] function approximation, Iteration , Unsupervised clustering and mathematical modeling. The basic concept depends on replication and decomposition ,since replication provide reusing phenomenon through which once a module is created and can replicates many modules in architecture. We observe in living organisms, our hands legs and even hairs can be replicated by module created once and decomposition feature provided will rearrange the modules depending of its functionality as cells function depends on integration of this modules. Modular systems allow for the reuse of modules in different activities, without having to re-implement the function represented on each different task (De Jong et al., 2004)(Garibay, 2004). Modularity has found robust feature depending on structural and functional activity of networks [10].which is an extension of the principle of divide and conquer leads subdivision of task into simpler subtask into modular neural systems Chiang and fu [11]proposed Divide-and-Conquer methodology which leads sub networks with their respective data for managing networks individually or serially and then integrated in a whole architecture which enables the decision on integrating sub networks for the appropriate outputs of individual for subnets into final output of the system.

B. Modular Neural Networks

The Urge for Modular neural network : The brain functions are been processes into individual functions, which are broken up into sub-processes to facilitate to execute in separate modules without mutual interference. [12] This information was first given by Happle and Murre which sequentially lead to the development in a long evolutionary process

The evolutions of modules in modular neural networks have high reflection of any living organisms, which raises the curiosity of research how the modularity is merged in natural phenomena .Wagner[13,14] have review many researchers proposing evolvability –stating the theories behind modular encodings. Recently a paper specifying theoretical the biology, give emphasize on the role of selection – pressure, explained in the modular organization. Lipson, kashtan and Alon[15] had brought numerical models indicating a rapid changes in evolution of modular systems[14] by designing modular encodings with different approaches as Gruau [16] Hornby [17] and Pollack [18] and Mouret and Doncieux [19] did through evolutionary programming to develop the natural modularity through tree-based representations. Doncieux and Meyer [20] and Reisinger.[21]] represented based on a number of modules, directly encoded, and outlined that how modules are connected. ”The executable pathway to biological networks “(Jasmin Fisher and Nir Piterman .Describes ‘Executable Biology” that dynamicity and ultimately explain how molecular function generates cellular function using modular neural networks

They suggestions appraised by developing a structure additional to modular artificial neural networks which are similar to the modular structure of the brain. This architecture can be applied in many real scenarios including day to day activities also. An inspiration of modular neural network architecture is to build a hug network by using modules as building blocks. All modules are neural networks. The architecture of a single module is simpler as that off sub-networks which are smaller than a monolithic network. Due to the structural modifications the task -module has to learn in general becomes much easier than the whole task of the network. This formulates easier to train a single module. In a additional the modules are connected to a network of modules moderately to a network of neurons. The modules are independent to work in parallel.

Many researchers have being researching how to generalized the large networks into smaller networks , the result of these is Modular neural networks .Which divide the hug network into the simple smaller networks into modules which exhibits the architecture of neural networks [22] , the major task to be accomplished is how to interconnect the modules in the Modular neural networks

The major aspect of modular neural networks revolute around the how to form modules , simple interconnection of modules, which is based on the communication of modules between them, the task performing is parallel processing , is it fault tolerant and learning ,has the ability to generalized to perform complex tasks to whole architecture .

C. Modular neural network Designing

The major contents of designing Modular neural networks are forming of modules, followed by learning of modules and then combining different modules for complete networks. More investigation has been done on module formation, module communication (interaction) and module reuse during evolution for a variety of classification and prediction tasks [23.]

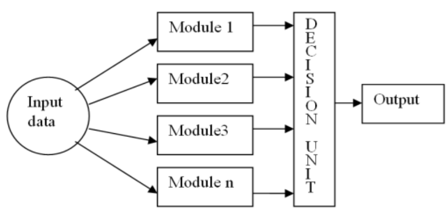

Figure 1. Modular Neural Network (MNN) architecture

D. Modular Neural Network Designing Requirement

Modular neural network design starts with the analysis of problem to be solved, according to the approaches. Basically there are two major 1. The Connectionist Approach and 2.The Weightless Logical Approach

Connectionist Approach

Connectionist approach is applicable to neural computing where a simple processors, known as neurons are interconnected to form biological nervous structure .Here the training is provided to solve the problem rather than programming .This approach was inspired by psychologist and biologist .A hug contribution was provided by MC CulloCh[49] and Pitts [50], Heb [51]and Rosenblatt [52] for parallel and interconnection of neural networks. Training and learning is applied to this architecture

Weightless Approach

These approach provides logic to neural computing, here the data is stored as part of patterns .In this approach the neural network has no weights , due to which the training is done fast and learning algorithm is extremely simple but this approach doesn't support biological and psychological model.

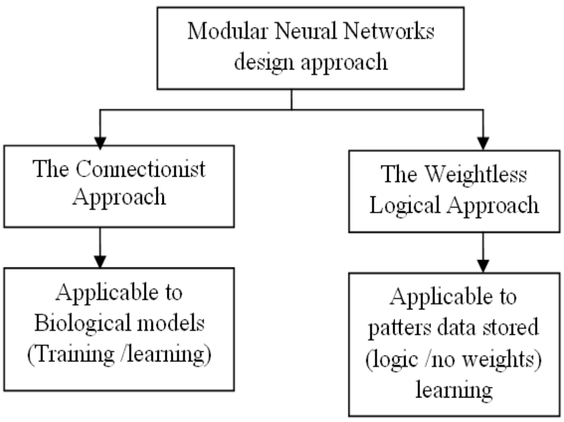

Figure 2. Modular Neural Network (MNN) design

III. RESULT AND DISCUSSION

A. Modular Neural Network Designing Requirement

Modular neural network first proposed by Jacobs, Jordan, Nowlan and Hinton [24,26,27,28], It mainly deals with what type of architecture should be used for formation of module (i.e **Task decomposition)** depending on the input/output relation of a particular problem , it does have any specific technique for it. Naturally it can be attained, mostly used architecture are (MLP,LNN,SOM,ART1,ART2) describes that the complex problems is solved by dividing it into simpler problems through "Divide and Conquer" algorithms by Chiang and Fu [25] is applicable to the architecture built out of sub networks able to manages a subsets of the data and depending on its **Modularizing learning** ,the relevance task is decomposed and distributed over sub-task separated in modules deals with determination of the number and size of individual module in the Modular neural network(MNN). Decomposing of classification task entails clustering (grouping)and then a separate classifier can be applied to all groups. Finally the integration engine that determines which is According this algorithms it states that the connections between nodes, called weights, carry activation levels from one neuron to another or to itself. According to the interconnection scheme used for a neural network, it can be categorized as (feed-forward, recurrent) and the integration Engine is trained to determine to which module should be considered.

Modular neural networks –Modules are connected to a network of modules rather than to a network of neurons. The modules are independent to work in parallel. For this modular approach it is always necessary to have a control system to enable the modules to work together in a useful way through **Training algorithm** for increasing ability to generalize the network.

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable.

B. Design Structure

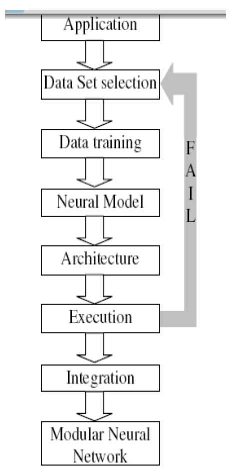

Figure 3. Modular Neural Network (MNN) design structure

Formation of Modules

The first step in designing MNN is formation of modules or Task decomposition, here the input data is naturally defined in a module .As it has to undergo the feasibility by training and learning phenomena to reduce error. Ishi describes the learning for modular structured networks ,that overcomes the problem of training hug networks

Combining of modules

Integration of module is very important task to be performed

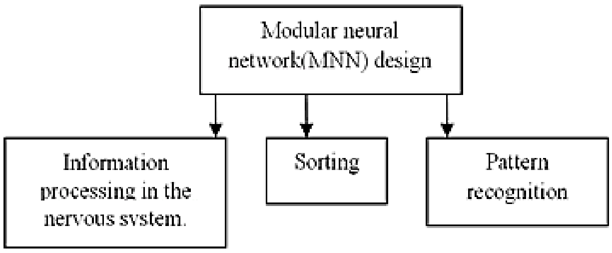

Figure 4. Modular Neural Network (MNN) design structure

Modular neural networks are inspired by biological concepts, which is simulates through defined architectures. Basically to solve complex problems ensemble-based and modular 29, 30 was introduced .In ensemble architecture, the neural networks can be formed with arbitrarily unstable set of initial weights, with different topologies followed by training 31, 32, this architecture is applicable in the field of classification, function approximate and learning mechanism 33, 34, 35, 36 through boosting algorithm is been used 37, 38 more enforces is given to initial weights varying with varying topology of training data set of neural network .The main advantage of using this architecture was linear combination of the outputs of the particular sub-neural network(39, 40, 41, 42, 43, 44, 45, 46, 47, 48)the result of these combination is distribution .Another architecture, which uses both supervised and unsupervised learning in sequential order is Decoupled modules architecture 53.In this architecture first stage, an adaptive resonant theory (ART) network was proposed by G. Bartfei 59, here the input data is decomposed into its inherent clusters in an unsupervised way as once the input data is classified in a each module .Individual modules is learned and then trained in parallel using supervised learning .There is no communication between modules results in input –output model

VII. EVOLUTIONARY APPROACH TO THE DESIGN OF MODULAR ARCHITECTURES:

This approach is applicable to biological fields ,give rise to diversity at every level of biological functions .Here are some of the architecture inspire by evolutionary approach for Modular neural network(MNN)

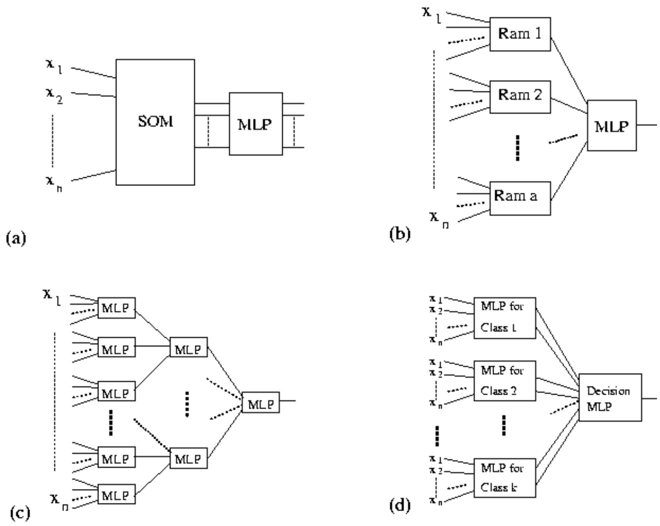

Figure 5. Some Examples of Modular Architectures

IV. CONCLUSION

The proposed MNN model has inconsistent advanced performance when the network topology is chosen optimally. However, the proposed MNN model has a drawback at some point of time. The connections between the modules depend upon the architecture, although it initializes to positive values at the beginning of the training phase, can change the output considering the desired output of the whole network. This problem can be resolved by an introduction of a more robust learning algorithm which ensures that the training algorithm [54, 55, 56, 57, 58]can reduce the error of particular model execution without respect of working parallel or sequentially.

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