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Analysis of Knowledge Based Artificial Neural Network and Its Applications.

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Abstract : This paper aims to demonstrate that basic structure of Neural Network and hybrid learning with their needs of Knowledge Based on Artificial Neural Network (KBANN).KBANN and worked in rules based on domain theory's with refinements translation rules system. For exploring the behavior of neural network and KBANN they link others each and like to transform the information's into the computational finite state language as a human brain neurons. It also describes various filed applications and their performance.

***Keywords* - KBANN, Neural Network, Hybrid learning, Applications**

I. INTRODUCTION

ANNs based on system is a system of modeled loosely on the human brain where knowledge is stored in the interconnected processing the training processing elements called neurons.During the training process learned knowledge distributed in the weight of different neurons where the ANNs operate systematically.ANNs information is sub symbolic and black box level. The extracting problem is learned knowledge network is comprehensible from received great deals of attention[1],[2],[3].Knowledge based on artificial neural network (KBANN) are among the leading paradigms in this venue(Towell and Shavlik 1994).the neural network approach in many aspects. The knowledge of a neural network lies in its connections and associated weight where the knowledge based on rule system lies in rules. Artificial neural network supports the system using knowledge oriented approach to aid selection of a course career. The KBANN represents as a simple knowledge proportional domain theory to an initial neural network containing the knowledge from the rules. Recently the KBANN system [4], addresses the problem by using domain knowledge to select a promising configuration for a neural network

The effective domain such as recognitions' [4,5] even when the initial domain theory is not particularly correct. The knowledge based on expert system technology that has been concentrating on the constructions of high performance programs in specializations and limited domain. Lopez et al.Multilayer feed forward ANNs used to extracted wavelet feature for classifications[6].the ANNs performs in a robust manner a data characteristics in a wide range, to decide a use of ANNs because their generation power[7].Rescharechers generally publish outside learning machine algorithm rather than the set of rules machine learning researchers transfer the domain theories. In the existing real world knowledge many of these algorithm maintain some sense of state ,so this makes a easier to use a machine.emprical leaning method for the supervised learning problems, due to this high cost and difficulties of obtaining domain knowledge[8],[9],[10]. The network is refined using standard neural learning algorithm a set of classification training, a successful explosive growth in the hybrid intelligent system in many diverse areas such as robotics [11],medical diagnosis[12],natural language understanding [13] industrial equipment [14] manufacturing control[15] and various applications[16].

This paper is divided into VIII Section: I Introduction, Section: II General Overview of KBANN, Section: III Finite State System, Section: IV Various Applications of KBANN, Section: V Future Work of KBANN. Finally, Section: VI Conclusion.

II. General overview of KBANN

KBANN consists of two independent algorithm a rule to network translator and refine that is a learning neural algorithm. The knowledge based on artificial neural network are combined in the form of sigmoid unipolar neurons, present their knowledge applications of empirical learning[17].the implementing feature of empirical and semiemprical functions the modeling of KBANN network that can be used in case of trail which would be small MLP network training [18,19].In back propagation algorithm insertion and refinement use rule to initialize architecture of multilayer neural network in a symbolic knowledge based on refine rules network is a large problem of back propagation system [20,21,22].the topology of network created by KBANN as well as the initial link weight of the network defining network in this way, the translation specifies the features that are probabaly relevant to making correct decision .inserting knowledge into neural network the first step of KBANN is to translate a set of approximate correct rules. A multilayer percetron (MLP) neural network chosen for its ability to approximate arbitrary nonlinear decision boundaries and to generalize is good choices a classifier in this context .one recent effort the KBANN system [23], addresses this problem by using domain knowledge to select a promising configuration for a neural network .This approach is used to determine the topology of the network and basis the network so that it will start a good set of weight. The connectionist weakens approach the date that is in inability to modify their network architecture hybrid system should be superior in terms of classification accuracy to empirical learning system.

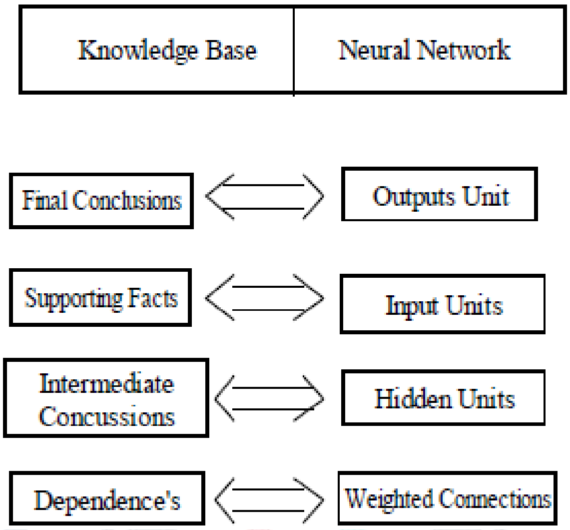

Figure1: KBANN

1. Neural Network

An Artificial Neural Network is an information processing paradigm is that inspired by way biological nervous system such as breian.A trained neural network can be thought of as an expert in the category of information it has been given to analyses. KBANN such a hybrid intelligence system performance capability of travel work mode the choice of developed KBANN compared the traditional neural network models. Neural network structure found by the Wikon and Cowan[24],gupta Knopf [25].Two advantage of embedding expert knowledge into ANNs over standard ,first is knowledge based to generalize better than ANNs [26] second is knowledge based ANNs require few example to obtained the same result as standard ANNs[27].KBANN used for proportional rules in domain theory. The other mode of to derive power of computational from a combination of adaptive connections called weight layer topology and nonlinearities associated neuron. Is another rules provide to people[28,29],the feed forward neural network that are trained using the back propagation algorithm, therefore temporal most important component in cognitive behavior of any learning system[30].ANNs perform in a wide range of data characteristics to use ANNs since their generalization power[31].

$$\text{Net Input}_i = \Sigma \text{ weigth}_i \,{*}\text{Activation}$$
$$j \pounds \{\text{Connected unit}\}$$
$$\text{Activation} = 1 / 1+ e^{-(\text{Net Inpu } i - \text{Bias } j)}$$

When the net incoming activation to unit exceeds its bias then the unit has activation near otherwise the unit has activation near zero.

2. Basic Structure of ANNs

Neural network are arrange in layer, each layer in a layered network is like a array of processing elements or neurons. The information flows through elements each in an input and output in right way. In order to generate ably the control input so that the system output trajecectory follows an optimal path between arbitrarily specified initial and final output a state one has to train a multilayer perceptron like neural network [32].The idea is originally based on the knowledge based artificial neural network (KBANN) which performs interpolation in the rules space of an expert system. It is interesting to note that at least theoretically the neural network is semi infinite dimensional [33],[34] in the sense that it is a mapping between the finite dimensional output space and the infinite dimensional space. In most cases ANNs is an adaptive system that change its structure based on external or internal information flows through the network during the learning phase. Multilayer Perceptron (MLP) network of processing element with only one hidden layer, but there is no restrictions on the number of hidden layers. KBANN performs is well when much of domain theory is known a restricted to discovering new rules. Having to translate the rules into neural network, back propagation modified algorithm is used.

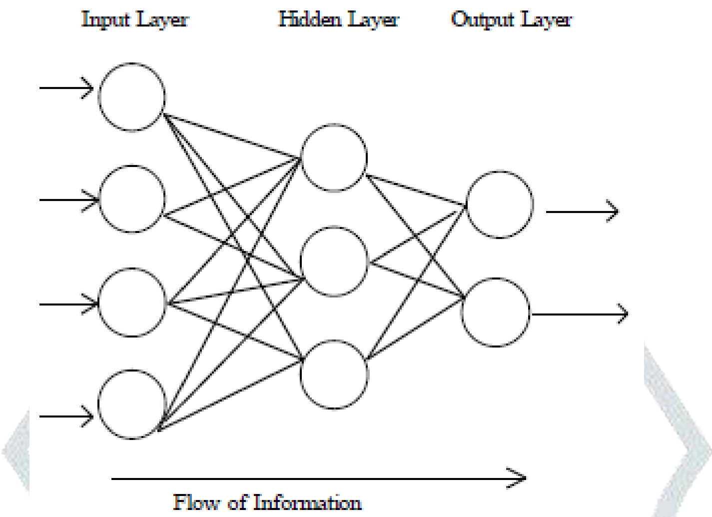

Figure 2: Multiflow layer

3. Human Neurons to Artificial Neurons

The neural network first training to introduce the essential feature and ANNs are computational paradigm with initial inspiration rooted in biology [39],of neurons and their interconnection. The ANNs frame work entails a large number of inter connected processing element or node called neurons. An artificial network consists of a pool simple processing unit which communicates by sending single to each other over a large number of weight connections.

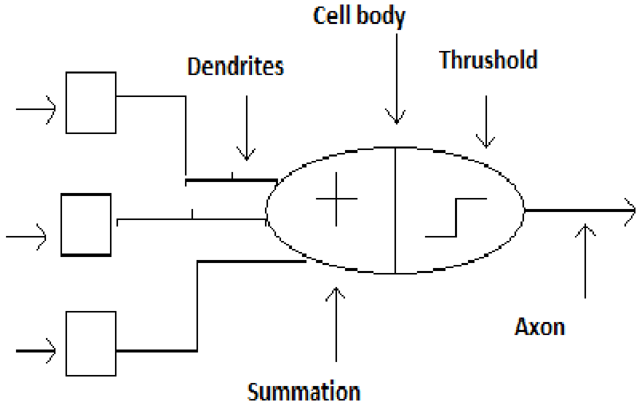

Figure 3: Artificial Neurons

Various studeis of different ways to build the artificial neural network and to exract encoding hypothise have been made[40,41]. The method used in manytechniques translation between a logic progarmming language and ANNs.The kbann able to recover the incorrect domian rules.

III. Finite State System

In the finite state the combing rules based reasoning with neural network system .KBANN typically employ a MLP neural network to capture and refreshment the knowledge embedded into a rakes base KBANN translate a domain theory represented as simple rule into promising initial neural network. They represent of FSA to KBANN in concept of series scanning input and track of state, the input is done with the help of Net talk system [35].KBANN takes a set of input propositional non recursive rule, input values is around the central value.

The domain theory back propagation refines to correctly classify with any training example not already covered. These connections allow the system learn new antecedents to rule that might have been not been part of original domain theory. The resulting networks using trained back propagation [36], KBANN is applied for real world problem in the domain of the molecular biology. After setting weight and bias of the unit in the network KBANN connect to each unit to any unconnected units at next lower level in the network using a small weight link.

1. Design Standard of KBANN

KBANN consists of two distinct algorithms the first covert the rule base into a feed forward network and the second is algorithm redness the neural network as a classifier has a layered structure with input layer and one output layer. Task domain the hybrid neuron symbolic system KNABB [37] exploit their capacity to use at same time theoretical knowledge and empirical knowledge. Typically one hidden layer and one output layer, each layer has a number of computational nodes or neuron operating in parallel. Moreover the process perform incrementally instead using the back propagation algorithm base on static network standard KBANN [4]. A domain theory expressed simple rule and translate it into a corresponding network with initial weight. Towell and Shavlik [38], introduce the knowledge based Artificial Neural Network algorithm that transforms a knowledge base into ANNs.The performance is compared with many popular learning algorithm as well as hybrid learning. The empirically compared pair of rule KBANN network with back propagation, hybrid system the domain theory is transfer an initial network through an extended version of KBANN.

A :- B,C A:- B, not D

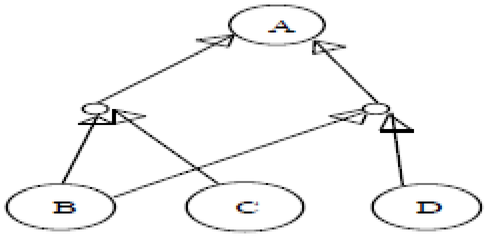

Figure 4: Transformation Rules

Symbolic knowledge coding positive link and solid line negative line is dash line. The binary inputs are B, C, and D units. Unit A is active when hidden unit is active, hidden units is correspond to rules. The second is active if B is active and dish not active, then first is active when and C are active.

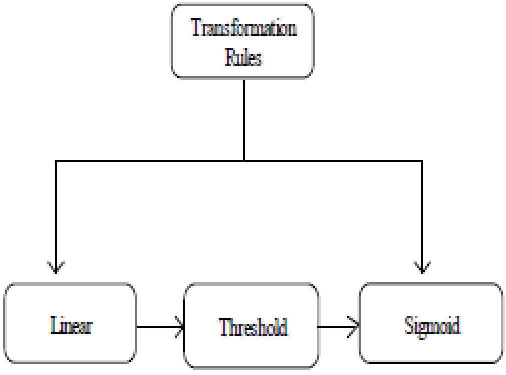

Figure 5: Translations Rules

2. A Hybrid Architecture Needs

In modern year the development of hybrid intelligence is so fast and their uses in different areas likes as medical diagnosis[42],robotics[43], language understanding [44], industrials equipment [44], manufacturing control [45] and financial

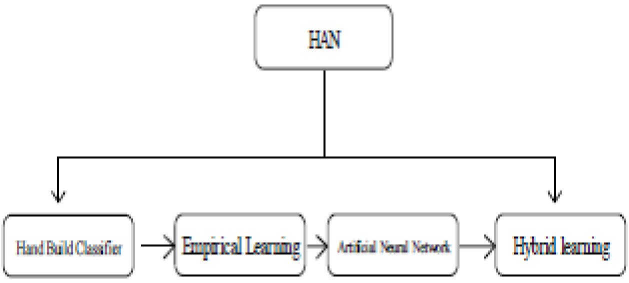

Figure 6: Hybrid architecture

application [46]. Before describing KBANN we further motive the development of hybrid system by listing some of the important weakness of hand built classifier and empirical learning system in the last decade researchers started to realize that rule based system and neural network are just to end of a whole intelligence [47]. The hybrid approach consider in this article takes the domain knowledge starting for network architecture.

Hybrid learning there is significant between the knowledge intensive learning by being told approach of hand built classifier and the virtually knowledge free approach of empirical learning. There are several possible ways to describe the feature of hybrid system based upon functional and the degree of interconnectivity.

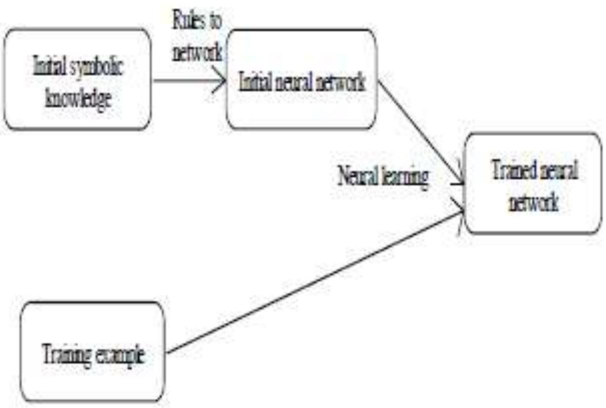

Figure 7: Refinement by KBANN

3. Learning of hybrid in KBANN

In a large reason of KBANN superiority in other system has been attributed to both its unyinderlying learning algorithm back propagation and its effective use of domain specifies knowledge (Towell 1992).The main difficulties of funding domain knowledge due to high cast [48],[47],[49],now the inductive learning performed through the training of the generated ANNs based on available data using a punishment and reward algorithm developed multitask learning (MTL).In which trained a network on several task taken from same domain in parallel, with single output unit for each task. A neuron psychology next growth of connectionism from influence, according to Lashely [50], that learning distributions process was important toward connectionist research. Learning is the conceptualization is the process of modifying connection weight to achieve correct inference behavior in a knowledge base system issue of learning deal with acquiring new knowledge and maintaining integrity of the knowledge base.

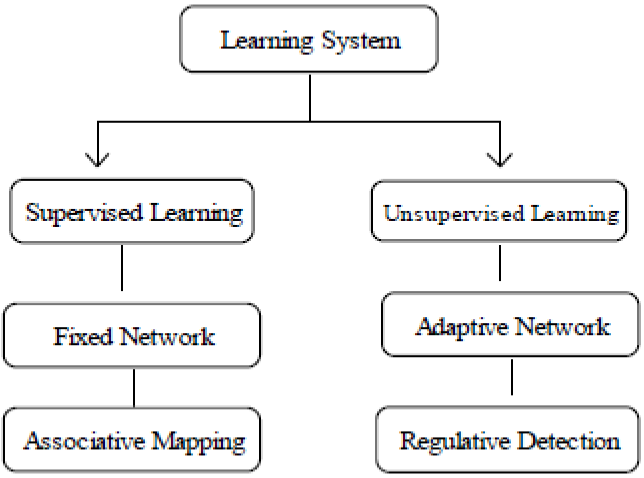

Figure 8: Learning Method

Temporal logics, an important component of cognitive behavior of any learning system [51]. A neural network is highly parallel machine consist of computational unit based originally the simple binary model of neuron McClloch and Pitts [52],the main purpose a set of weight which minimize the error one well known method which is common to many learning paradigm is last mean square (LMS) convergence.

4. Improving Performance Analysis of KBANN

The KBANN topology for instantiated resembles that of adaptive mixture of local experts [59], computational framework might be easily adopted for the KBANN architecture being explored in the current context. Now we analyzed the performance of KBANN have to improve its training time and generalizations capability, two major aspects to improve the performance of KBANN given below:

1. Inductive Bias
2. Learning algorithm

Although more sophisticated learning algorithm available, backpropagation is used because of its simplicity and ease implementations. This was done by normalizations. The basic problem personalization is that are affected by context of the user. In additions a local based network effect less representations by catastrophic interference phenomena can learn incrementally [60].

Mitchell (Mitchell 1997) define bias for choosing one generalization over another than strict consistency with instances, the prior knowledge enriched by paradigm task that used to initialize network to use different learning adaptive system. The hole system able to adapt various set of hybrid learning domain knowledge to improve their performance ,the performance is basically depended on the prior and training inductive bias technique,randomaly choose one to assign weight for good staring weight space to leading convergence. KBANN performance also profile without performances' also profile without any such as further training on finite state knowledge bade artificial neural network. Inductive bias depends on the applications the training data and the network architecture.

IV. Various Applications of KBANN

Broad applicability to real world business problem and there field. Artificial neural network are used in different application such as control [53],[54],system analysis and diagnosis[55],[56],in fact they have already been successfully applied in many industries. ANNs is also used in following specific paradigm recognition of speakers in communication diagnosis of hepatitis, recovery of telecommunication from faulty software interpretation of multimeaning .Chinese word undersea mine detection texture analysis three-dimensional object recognition hand written word recognition and facial recognition. If this hypothesis is correct then domain theory provided to KBANN need only approximately correct for it to supply useful information. In KBANN net hypothesis are relatively intensive to noise in domain.

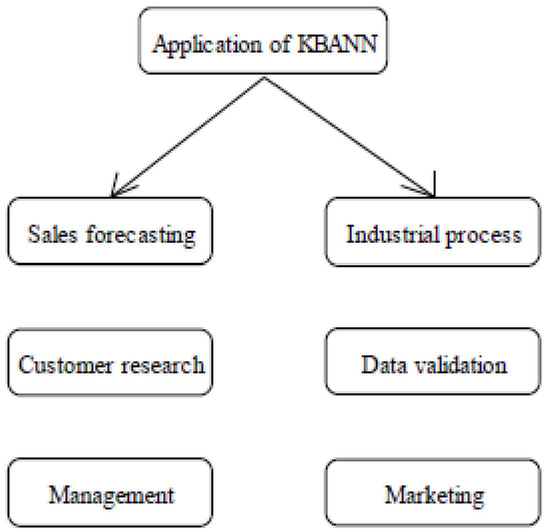

Figure 9: Application of KBANN

This hypothesis is test by systematically adding noise to domain theories in marketing application such as direct impact on the profitability of an airline and can provide a technology advantage for user of the system.

V. Future Work of KBANN

KBANN user a domain theory to give a network a good set of initial weight space. Another venues where a KBANN type hybrid approach might be useful is the domain rule generation. A trained KBANN could be analyze to extract refined rule to reconstructs an improved knowledge base[57].The KBANN algorithm generally produce better result than others with an initial proportional domain theory and training data since they also change the topology is to in efficient to make use of purely inductive method will also be consider in addition .almost all of the details reported in above should be repeated with an artificial domain for which the theory and relevant feature are known with certainty. For instance an artificial problem would allow a closely controlled experiment on the effect of irrelevant and missing antecedents.

VI. Conclusion

Artificial Neural Network and Knowledge Base Artificial Neural Network they are corresponding to each other. its provided the various flow of biological and human brain computational informations,to understand the hybrid architecture and learning hybrid system with translation of refinement domain theory. In this paper concisely described the how training time and correct algorithm in different cases obtained between KBANN and Artificial neural network systems. To explored the ideas of advanced adaptive technique to determine the weakness of ANNs and others rules based systems. KBANN given that a responsible result in computational algorithm difficulties.

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