Meta-cognitive Neural Network-A Literature Review

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Abstract— **In this review paper, we review the different classification of Meta-cognitive Neural Networks. Classification is an important concept of Data Mining. Data mining deals with the two types of learning that includes supervised learning and unsupervised learning. The network, referred as Meta-cognitive Neural Network (McNN). McNN are made up of two components. The two components are named as the cognitive component and the meta-cognitive component [1]. Meta-cognitive learning is a machine learning concept which has involves the learning techniques. That learning techniques are what-to-learn, when-to-learn and how-to-learn. Neural networks are also included for classification [2]. Different machine learning techniques are implied in classification for better accuracy and time efficiency.**

Keywords — **Meta-cognitive learning, Sequential learning, Multi-cognitive classification problem and Data Mining.**

I. INTRODUCTION

The awareness and knowledge of one's mental processes such that one can monitor, regulate and direct them to a desired goal –As defined by J.H Flavell (1976). Data mining (Knowledge Discovery) is the process of analyzing data from different perspectives and summarizing it into useful information. Using data mining the data can be classified, clustered, associated and finding patterns. Learning in data mining can be classified as supervised learning and unsupervised learning. Supervised learning is learning contents on some fixed rules whereas unsupervised learning is learning using some measures such as distance etc. Classification of data plays a vital role in research which can be used for prediction and comes under the category of supervised learning. There are various methods of classification such as decision tree, Naïve Bayes, neural networks etc. Neural networks are framed based on the neuron structure of the human brain. While learning the new concept the brain may not be aware what it is. If training is given on the new dataset repeatedly then learning is made quicker. This concept is used for classifying data using machine learning. The dataset will be divided into training and testing. The training dataset contains the features and the class it belongs. The machine learning algorithms are used to train the neurons based on the values of the training dataset. If the neurons are repeatedly trained with the dataset then it can predict the dataset which is given as test data.

Recent studies in human learning suggested that the learning process is effective when the learners adopt self-regulation in learning process using meta-cognition. The term meta-cognition is defined as, one's knowledge concerning one's own cognitive processes or anything related to them". Precisely the learner should control the learning process, by planning and selecting learning strategies and monitor their progress by analyzing the effectiveness of the proposed learning strategies. When necessary, these strategies should be adapted appropriately. Meta- cognition present in human-being provides a means to address what-to-learn, when-to-learn and how-to-learn, i.e., the ability to identify the specific piece of required knowledge, judge when to start and stop learning by emphasizing best learning strategy. Meta-cognitive Neural Network classifier is capable of deciding what-to-learn, when-to-learn and how-to-learn the decision functions from the training data. [1][2][3] Metacognitive Neural Network (McNN) classifier which employs human-like meta-cognition to regulate the sequential learning process. In this paper section II describes the methods and the dataset, section III discusses the experimental results and section IV concludes the paper.

II. META-COGNITIVE NEURAL NETWORK:

In this section, we present the architecture of the Meta cognitive Neural Network (McNN) classifier and its working principles. McNN architecture is developed based on the Nelson and Narens meta-cognition model. The information flow from the cognitive component to metacognitive component is considered monitoring, while the information flow in the reverse direction is considered control. McNN has two components namely the cognitive component and the meta cognitive component. [4][5]The cognitive component of McNN is a three layered feed forward radial basis function network with Gaussian activation function in the hidden layer. The meta-cognitive component contains copy of the cognitive component. When a new training sample arrives, the meta-cognitive components of McNN predicts the class label and estimate the knowledge present in the new training sample with respect to the cognitive component. Based on this information, the meta-cognitive component selects a suitable learning strategy, for the current sample. Thereby, addressing the three fundamental issues in learning process: (a) what-to-learn, (b) when-to-learn and (c) how-to-learn [6].

III. MODELS OF METACOGNITION

A. Nelson and Naren Model

• Cognitive component
• Represent the knowledge
• Metacognitive component
• Represent dynamic model of the cognitive component
• Signals – Control
• Change the state of cognitive component or cognitive component itself
• Initiate, or terminate or continue – Monitory
• Inform about cognition

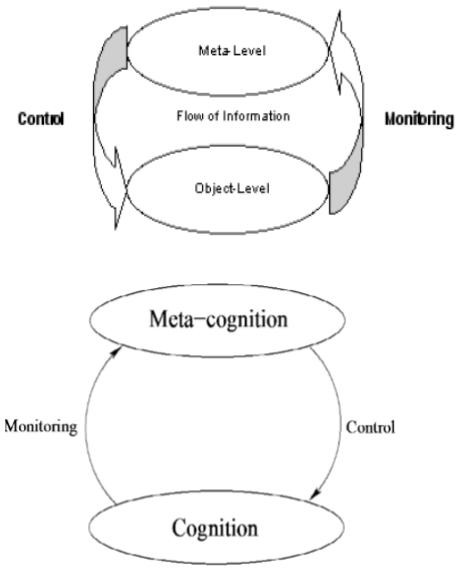


Fig.1 Nelson Naren's Model

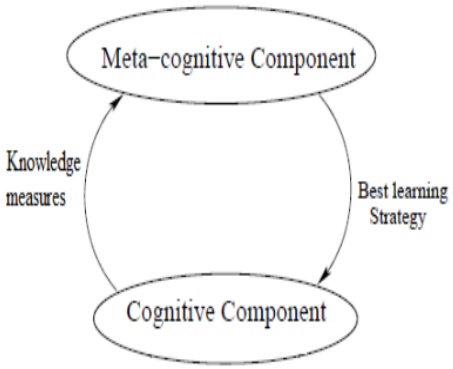
B. Meta-cognitive network

1) Cognitive component

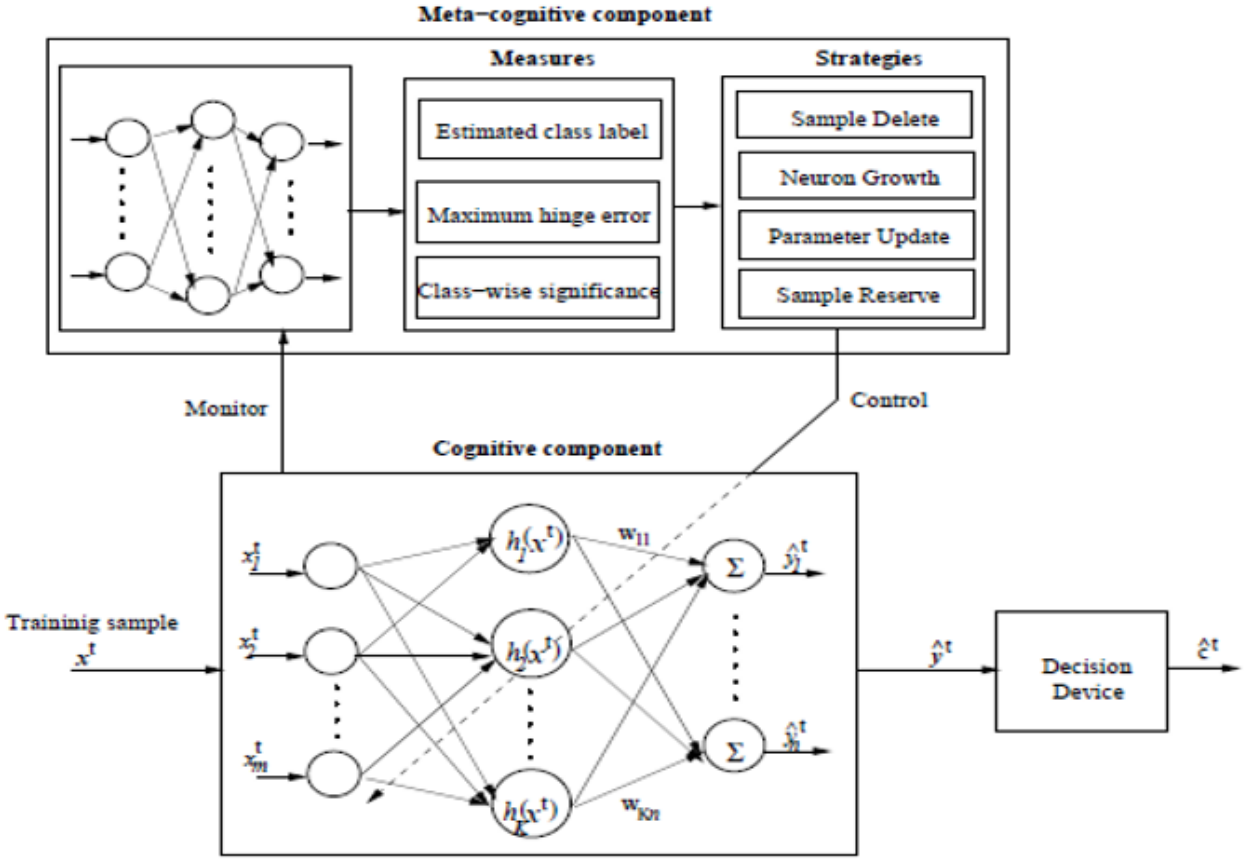
• Representation of knowledge
– To be learnt from the sample stream
– Unknown
• Suitable structure and its parameters
• Choice of knowledge representation
– Neural network : RBFN
– Neuro-Fuzzy
– Complex-valued neural network
– etc..

2) Meta-Cognitive component

• Learning about learning
– Decides
• What-to-learn
– Proper choice of samples from stream based on current state of knowledge
• When-to-learn
– Appropriate usage of sample in right interval
• How-to-learn
– Structure modification
– Parameter learning



IV. MCRBF: SCHEMATIC DIAGRAM



V. MCRBF: META-COGNITIVE COMPONENT

• Control signals
– Sample Deletion Strategy
• Remove similar samples as that of knowledge stored in the network
– Sample Learning Strategy
• Learn the current sample by any of the following way
– Neuron Addition: Add new resource to capture novel knowledge
– Neuron Deletion: Delete redundant resource
– Parameter Update: Update existing knowledge
– Sample Reserve Strategy

• Current sample contain information but I will learn it later

VI. SEQUENTIAL LEARNING ALGORITHM

• Projection Based Learning for a Meta-cognitive Radial Basis Function Network (PBL-McRBFN):
– What is Projection Based Learning?
• Evolving learning algorithm
• Classifier based on Hinge loss error function minimization
• Based on the best human learning strategy, namely, selfregulated learning.
• Uses past knowledge in learning
• Fast learning algorithm:
– Input parameters are initialized through meta-cognition
– Output weights are estimated as a solution to a set of linear equations as a linear programming problem.

VII. OBSERVATIONS

• First time in literature, human metacognition principles are integrated in machine learning framework.
• Self-regulation of cognitive component (RBF network) helps in achieving better generalization.
• Sample reserve strategy
• Play vital role in Judgment of Learning
• Use self-selected samples for validation of addition of neurons
• One can also use it for preventing drift in sequential learning.

VIII. NEURO IMAGING IN AD

- MRI - Magnetic Resonance Imaging
  – High spatial resolution
  – Exceptional soft tissue contrast
  – Can detect minute abnormalities
  – Can visualise and measure atrophy rates
- Advanced MR techniques
  – Diffusion Tensor Imaging - Tissue microstructure
  – Magnetic resonance spectroscopy - Brain metabolism
  – Functional MRI - Neural activity
- Early detection of AD from MRI is a promising alternative

IX. CONCLUSIONS

This paper gives an overview of different meta cognitive techniques for classification. Depending on the type of learning such as batch, sequential and incremental the method of classification can also be selected. The working nature of the machines differs from each other which were discussed in this paper. The method of learning changes from one machine to the other. Due to this the efficiency of the experiments gets varied. The table gives the comparison of the efficiency of different algorithms on different dataset. This paper can be concluded that for classification problems using meta cognitive concept McELM performs well when compared to McNN. For the first time, human metacognition principles are integrated in a machine learning framework. Self-regulation of cognitive component (RBF network) helps in achieving better generalization. McRBF effectively answer what-to-learn, when-to-learn and how-to-learn by --Sample deletion strategy – Sample learning strategy. Addition/deletion and update – Sample reserve strategy.

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