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Parkinson's Disease Classification using Various Advanced Neural Network Classifiers

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Abstract: This paper proposes the application of Online Meta-neuron Based Learning Algorithm (OMLA), Self adaptive Resource Allocation Network (SRAN) and Projection Based Learning Meta-cognitive Radial Basis Functional Network (PBL-McRBFN) for Parkinson's disease classification. This is the first journal paper to apply the concept of OMLA, SRAN and PBL-McRBFN for Parkinson's disease classification. Online Meta-neuron based Learning Algorithm (OMLA) is a newly evolved network applied for Parkinson's disease classification. This classifier make use of both global and local information of the network. Self Adaptive Resource Allocation Network (SRAN) consists of self adaptive control parameters that changes training data sequence, develop network architecture and learns network parameters. Also, repeated learning samples are removed with the help of this algorithm, hence training time and over flow problems can be minimized. The Projection Based Learning algorithm determines the output parameters of the network such that the energy function is minimum. The result shows the comparison of efficiency for the three networks in classification of Parkinson's disease.

Keywords : Online meta-neuron, Projection based learning, Resource Allocation Network, Self adaptive control parameters.

I. INTRODUCTION

Parkinson's disease is a progressive nervous system disorder that affects body movements, including speaking and writing [11]. Symptoms develop in a gradual manner and may start with slight tremors in hands. Some patients may have tremor as their primary symptom, while others may not have tremors, but have balancing problems. The primary motor symptoms are slow physical movements (bradykinesia), shaking (tremor), muscle stiffness (rigidity) and postural instability (impaired balance and coordination). People with Parkinson's disease also experience stiffness, cognitive problems, neurobehavioural problems, sleep difficulties and also they cannot carry things in hands.

The symptoms of Parkinson's disease are caused by the loss of dopaminergic cells in the part of brain called Substantia Nigra. These cells are responsible for producing Dopamine which is a neurotransmitter. Dopamine helps to transmit messages from brain that controls and coordinates body movements. It allows Substantia Nigra and Corpus Sriatum which is an another area of brain to communicate for proper muscle movement. If the Dopaminergic cells in the brain are damaged, then dopamine production goes down and messages from the Substantia Nigra and the Corpus Striatum do not work properly.

Online Meta-neuron based Learning Algorithm (OMLA) is a special class of artificial neural network (ANN), where neuron models communicate with spikes. Spiking neurons are capable of processing data using a relatively small number of spikes. The spiking neural network architecture with a concept of meta-neuron includes all the pre and post synaptic neurons present in the network. In this paper, Online Meta-neuron based spiking neural network have been applied to classify parkinson's disease. The meta-neuron based learning rule uses both local and global information present in the network to perform one shot weight updation of the synapses [3].

Self adaptive Resource Allocation Network (SRAN) classifier is a feed forward network. SRAN learning algorithm begins with zero hidden neurons and adds new hidden neurons based on the information present in the current sample. It also learns by improving network parameters. These self adaptive control parameters control the order of training pattern and also identify the pattern 't' with more knowledge. Incase the learning condition is not met by the pattern 't', then the pattern is stacked at the end of the order for learning later [10].

Projection Based Learning Meta-cognitive Radial Basis Functional Network (PBL-McRBFN) works by determining output parameters such that the energy function is minimum i.e, the network achieves the minimum point of energy function. The algorithm involves four strategies such as sample delete, neuron growth, parameter update and sample reserve. In PBL-McRBFN, sample delete strategy addresses what-to-learn by deleting insignificant samples from training dataset. Neuron growth strategy and parameter update strategy address how-to-learn by which the cognitive component learns from the samples. And then sample reserve strategy addresses when-to-learn by presenting the samples in the learning process depending upon the knowledge present in the sample [6].

This paper is organized as follows: Section II briefly describes the data set information. Section III describes OMLA, SRAN and PBL-McRBFN classifiers. Section IV describes the results from this study using OMLA, SRAN and PBL-McRBFN classifiers. Section V summarizes the conclusion.

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II. DATA SET INFORMATION

The Parkinson's data set is a voice data set which consists of sound readings recorded from 23 Parkinson's patients (PD) and 8 healthy people [9].

It contains two classes, 22 features with 195 samples and it is taken from UCI repository [5]. The ultimate objective of the network is to classify healthy control subjects from Parkinson's patients, as per the status provided in the data set. The status is assigned as 1 for PD and 2 for healthy control subjects. The table-I describes the details of the data set being used for classification. The data set has been separated as 80% (156 samples) for training and 20% (39 samples) for testing [11].

Table-I: Dataset information

Dataset character -istics	Area	Attribute Character-istics	No. of attributes	Samples	
				Training	Testing
Multi-variate	life	real	22	156	39

III. PROPOSED METHODOLOGY

The block diagram for application of Projection Based Learning Meta-cognitive Radial Basis Functional Network (PBL-McRBFN), Self Adaptive Resource Allocation Network (SRAN) and Online Meta-neuron Based Learning Algorithm (OMLA) for classifying Parkinson's data set is shown in fig. 1. The detailed description of the classifiers are described as follows:

A. Online meta neuron based learning algorithm (OMLA)

The OMLA network consists of two layers which are used for pattern classification. Learning of network takes place in online manner. The basic architecture OMLA network is shown in fig. 2. The OMLA employs a meta-neuron with memory that stores only those spike patterns which are used to add a neuron to the network. It can decide whether to do neuron addition or parameter updation or spike deletion. The presynaptic neurons in the network are also connected to a single meta-neuron which allows the meta-neuron to access the local information present in the input spike patterns. Further, the meta-neuron can access the global information stored in the network as synaptic weights of the postsynaptic neuron. The concept of the meta-neuron is inspired by the hetero synaptic plasticity induced by astrocyte cells in biological systems [3].

Strategies of OMLA

OMLA learns from input spike patterns in online manner i.e. training spike patterns are presented to the network one-by-one and only once. It chooses one of the three different strategies namely, neuron addition strategy, delete spike pattern strategy and parameter update strategy for learning a given input spike pattern [3].

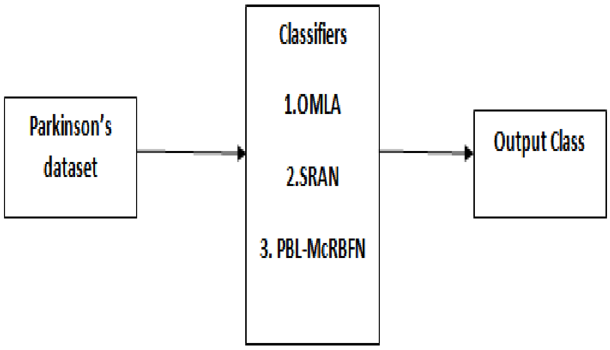

Fig. 1. Block diagram of proposed methodology

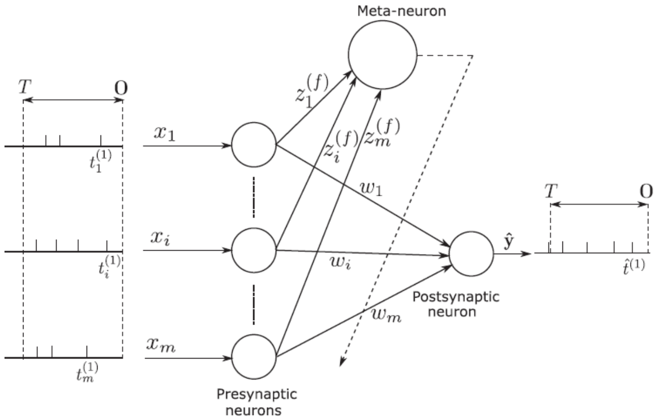

Fig. 2. Architecture of OMLA

a. Neuron Addition

A new neuron is added to the network when the current spike pattern contains a significant amount of new knowledge. The high value of $\hat{t}cc$ (Spike time of same class neuron) indicates that the information present in the network is not adequate to approximate the present input spike and hence a new neuron is added to the network.

If $\hat{t}_{cc} > T_n$, then a neuron is added to the network.

where, T_n is Novelty threshold time and $\hat{t}_{cc}$ is spiking time of same class neurons with minimum latency.

T_n is given by,

$$T_{n} = \alpha_n T + (1- \alpha_n)\, T_{ID} \qquad (1)$$

Where, α_n is Novelty threshold and T_{ID} is Target firing time.

b. Deleting Spike

If a neuron from the same class as that of the current input spike pattern fires closer to the target firing time (T_{ID}), then a spike pattern is deleted.

If ($\hat{t}_{CC} \leq T_d$) & ($\hat{t}_{MC}$ - $\hat{t}_{CC}$) $\geq T_m$, then delete the spike pattern.

$$T_{n} = \alpha_d T + (1- \alpha_d)\, T_{ID} \qquad (2)$$

where, T_d is Time based delete threshold, $\hat{t}_{MC}$ is Spike time of different class neuron with minimum latency, T_m is Time based marginal threshold and α_d is Delete threshold.

c. Weight Update

The learning algorithm updates the synaptic weights of existing neurons when none of the criteria for neuron addition and delete spike pattern is satisfied. The neuron spikes after weight updation is given as,

$$t_{CC} = \hat{t}_{CC} - \alpha_s \hat{t}_{CC} \qquad (3)$$

where, α_s is learning rate

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The weights of the MC neuron updation using meta neuron is given as,

$$\hat{t}_{MC} - \hat{t}_{CC} < T_m \tag{4}$$

where, T_m is margin threshold.

The desired spike time for the neuron MC after weight updation is given as,

$$t_{MC} = t_{CC} + T_m \tag{5}$$

B. Self adaptive resource allocation network (SRAN)

The fundamental unit of SRAN classifier is radial basis function (RBF). The basic building block of SRAN is shown in fig. 3. The self adaptive control parameters in proposed algorithm are fixed and problem independent. These parameters change the order by which the classifier relates decision function depending on the variance of knowledge present in each sample and in the network. The sample is involved in training, if the variance is larger. If it is smaller, then the sample is stacked at the end of the order for later learning. Similarly, the sample is deleted if it contains similar knowledge of the other. Therefore, the complete architecture is compact and provides better generalization [7].

Strategies of SRAN

Based on the magnitude and absolute phase error of each sample in the training sequence, the self regulating scheme performs one of the following actions [10].

a. Deletion

If the absolute maximum error $E = \max_{i=1,2,\ldots,n} |ei|$ is less than 0.05, then the sample is deleted without being used and thus prevents over training.

b. Growing

The following criteria must be met for an observation (x_t, y_t) to be used to add a new hidden neuron to the network.

$$C = \hat{C} \text{ and } E \geq \eta_a \tag{6}$$

where, E is absolute maximum error in the current sample and η_a is self adaptive growing threshold.

The growth control parameters are adapted based on the current sample error (e). Depending on the error that contributes to neuron growth, the respective growth control parameters are updated as,

$$\eta_a = \delta\, \eta_a - (1-\delta)\, E \tag{7}$$

where, δ is a parameter that controls the slope of decrease of control parameter.

A hidden neuron is added if the growing condition is satisfied. The parameters of newly added neuron are assigned as given in (8)

$$\alpha_{K+1} = e; \quad \mu^c_{K+1} = x_1; \quad \sigma^c_{K+1} = k\,\|x_t - \mu^c_{nr}\| \tag{8}$$

where, k is a constant that maintains the overlap of hidden neurons, nr is the neuron nearest to the current sample and c is the actual class label of the current sample.

After addition of new hidden neuron, the order of error covariance matrix $P_{(t)}$ is increased to,

$$P_{(t)} = \begin{matrix} P_{(t-1)} & 0 \\ 0 & P_0 I \end{matrix} \tag{9}$$

where, I is identity matrix, P_0 is estimate of uncertainty in the initial values assigned to the parameters.

The dimensionality of identity matrix is equal to the number of parameters introduced by the new hidden neuron.

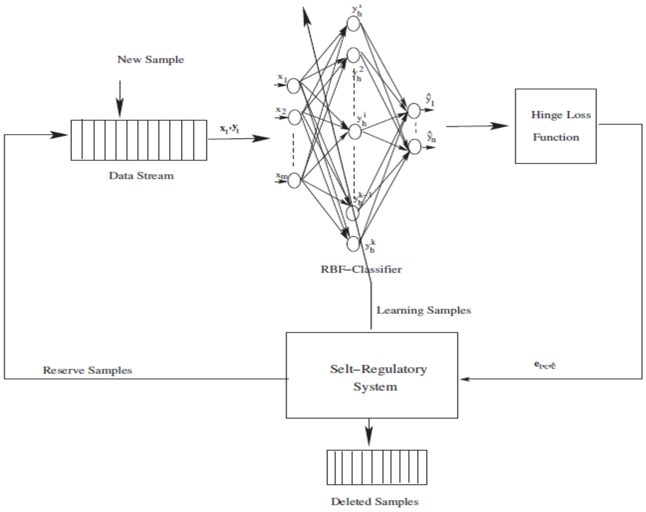

Fig. 3. Architecture of SRAN Classifier

c. Learning

The network parameters are updated if it satisfies the criteria given by,

$$C = \hat{C} \text{ and } E \geq \eta_l \tag{10}$$

where, η_l is self adaptive learning control parameter.

Here, the self adaptive learning threshold is adapted using (11) based on the knowledge present in the current sample.

$$\eta_l = \delta\, \eta_l - (1-\delta)\, E \tag{11}$$

where, δ is parameter that controls the slope of decrease of the control parameter.

d. Sequence altering

The samples are stacked at the end of the order, if the conditions for learning and growing strategies are not meet. These samples can refine the network parameters, when rest of the samples in the dataset are used. Any new sample arriving in the sequence is stacked behind the current last sample.

C. Projection based learning meta-cognitive radial basis functional network (PBL-McRBFN)

The cognitive component and meta-cognitive component are the two main units of this network. The basic architecture of PBL-McRBFN classifier is shown in fig. 4. The cognitive component is a three layered RBF network and the meta-cognitive component is its dynamic model. The meta-cognitive component identifies the sample and determines information in the sample. In accordance with this knowledge, meta-cognitive component directs the learning activity of cognitive component. The strategies of PBL-McRBFN network address to learn what, when and how in an effective way [6].

Strategies of PBL-McRBFN

PBL-McRBFN network works by determining output parameters such that it achieves the minimum point of energy function. The McRBFN has energy function as given by (12).

$$J(W) = \frac{1}{2}\sum_{i=1}^{t}\sum_{j=1}^{n}\left(y_j^i - \sum_{k=1}^{k} W_{kj} h_k^i\right)^2 \tag{12}$$

where, h_k^i is the output of k^{th} hidden neuron for i^{th} sample.

PBL algorithm for McRBFN classifier can be summarized as below:

1. For a given input x^t, the predicted output y_j^t of McRBFN is

$$\hat{y}_j^t = \sum_{k=1}^{k} W_{kj} h_{k,}^t \quad j = 1,2,\ldots,n. \tag{13}$$

where, h_k^t is output of k[th] hidden neuron to input x^t and w_{k_j} is weight of k[th] hidden neuron to j[th] output neuron.

$$h_k^t = \exp\left(\frac{-\left\|x^t-\mu_k^l\right\|^2}{\left(\sigma_k^l\right)^2}\right) \tag{14}$$

where, σ_k^l and μ_k^l are width and center of k[th] hidden neuron of l[th] class.

2. The meta-cognitive component directs the learning activity of cognitive component with the help of determined class name ($\hat{C}^t$), Extreme hinge error (E^t) and classwise importance (Ψ_c).

$$\hat{C}^t = \arg\max_{j\epsilon 1,2,..,n} \hat{y}_j^{\,t} \tag{15}$$

$$E^t = \max_{j\epsilon 1,2,..,n} \left|e_j^t\right| \tag{16}$$

$$\Psi_c = \frac{1}{k^c}\sum_{k=1}^{k^c} h(x^t, \mu_k^c) \tag{17}$$

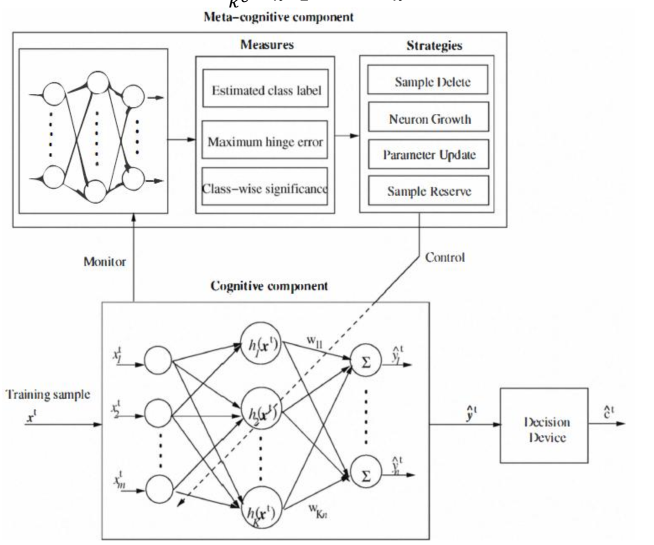

Fig. 4. Architecture of PBL-McRBF classifier

3. The meta-cognitive component directs the learning activity of cognitive component by choosing the appropriate learning activities.

a. Delete sample strategy

If $c^t = \hat{c}^t$ and $E^t \leq \beta_d$, then delete the sample from the training dataset without learning.

b. Neuron Growth Strategy

If ($\hat{c}^t \neq c^t$ or $E^t \geq \beta_a$) and $\Psi_c(x^t) \leq \beta_c$, then allocate a new hidden neurons in the cognitive component. The width and center of newly added hidden neuron are determined based on the intra and inter class distances of nearest neurons using (18), (19), (20) and (21).

$$\mu_{k+1}^c = x^t;\ \sigma_{k+1}^c = k\sqrt{x^{t^T} x^t} \tag{18}$$

$$\mu_{k+1}^c = x^t;\ \sigma_{k+1}^c = k\left\|x^t - \mu_{nrs}^c\right\| \tag{19}$$

$$\mu_{k+1}^c = x^t + \zeta\mu_{nrs}^c - \mu_{nrI}^l \tag{20}$$

$$\sigma_{k+1}^c = k\left\|\mu_{K+1}^c - \mu_{nrs}^c\right\| \tag{21}$$

Output weight parameters are estimated as,

$$\begin{matrix} W_K \\ W_{K+1} \end{matrix} = \left(A_{(K+1)\times(K+1)}\right)^{-1} B_{(K+1)\times n} \tag{22}$$

Also, the self-adaptive meta-cognitive addition threshold is updated using,

$$\beta_a := \delta\beta_a + (1-\delta)E^t \tag{23}$$

c. Update parameter strategy:

The network updates the output weight parameters of cognitive component and update threshold of self adaptive meta-cognitive component using (24) and (25) respectively, if $c^t = \hat{c}^t$ and $E^t \geq \beta_u$.

$$W_K = W_K + A^{-1}(h^t)^T(e^t)^T \tag{24}$$

$$\beta_u := \delta\beta_u + (1-\delta)E^t \tag{25}$$

d. Sample reserve strategy:

The samples are pushed into the reserve for later learning, if none of the criteria is satisfied.

4. The cognitive component executes the strategy for which the condition is satisfied.

5. Perform the process from 1 to 4 till all the samples in training data set are learnt.

The flow chart for the proposed method of classification of Parkinson's disease using OMLA, SRAN and PBL-McRBFN classifiers is shown in fig. 5.

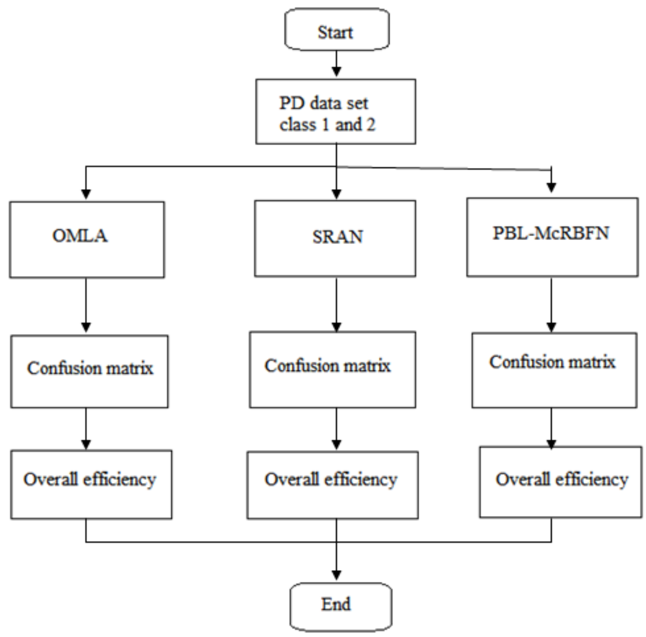

Fig. 5. Flow chart of proposed methodology

IV. RESULT AND PERFORMANCE MEASURES

In this paper, we have used overall efficiency as a performance measure. The statistical measures are represented as confusion matrix. The performance in percentage specifies the number of samples of a specific class have been accurately categorized. The overall classification efficiency of the network is given by,

$$\eta_o = \frac{1}{NT}\sum_{i=1}^{nc} q_{ii} \tag{26}$$

where, NT and nc are total number of samples and classes presented in the data set respectively.

Overall efficiency is defined as the ratio of number of samples accurately classified by the network to the total number of samples contained in the data set.

$$\text{Traeff} = \frac{\text{Number of samples correctly classified}}{\text{total number of samples}} \tag{27}$$

The table-II represents the overall efficiency obatined from OMLA, SRAN and PBL-McRBFN classifiers. The results of SRAN classifier has been obtained from [17]. It can be observed from the table-II that PBL-McRBFN classifier has better efficiency when compared to OMLA and SRAN classifiers because of the use of human meta-cognitive principles [6].

Table-II: Results of OMLA,SRAN and PBL-McRBFN classifiers in classification of PD data set

Classifier	Training Confusion Matrix		Testing Confusion Matrix		Training Efficiency (%)	Testing Efficiency (%)
PBL	67	2	82	1	99%	94%
	0	69	9	73		
OMLA	107	24	12	1	84%	81%
	1	24	6	17		
SRAN	63	6	76	7	80%	87%
	21	48	14	68		

V. CONCLUSION

This journal paper has presented a new approach for Parkinson's disease classification using OMLA, SRAN and PBL-McRBFN networks. OMLA is a sequential learning algorithm which involves all the pre synaptic and post synaptic neurons in the network. It is a single layered fast learning network which make use of both local and global information of the network for weight updation. Using self regulated control parameters, the self adaptive nature of SRAN algorithm identifies the reduced training data sequence and produces a compact network architecture with better generalisation. The performance of OMLA, SRAN and PBL-McRBFN classifiers have been studied with binary PD data set collected from UCI repository. Based on these studies, it can be concluded that PBL-McRBFN gives better classification efficiency than SRAN and OMLA classifiers due to the use of human meta-cognitive principles [6].

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