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Imbalanced dataset classification using fuzzy ARTMAP and computational intelligence techniques

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ABSTRACT

Recently, fuzzy adaptive resonance theory mapping (ARTMAP) neural networks are applied to solving complex problems due to their plasticity-stability capability and resonance property. An imbalanced dataset occurs when there is the presence of one class containing a greater number of instances than other classes. It is skewed representation of data. Many standard algorithms have failed in mitigating imbalanced dataset problems. There are four paradigms used-data level, algorithm level, cost-sensitive, and ensemble method in solving imbalanced dataset problems. Here we put forward a method to solve the imbalanced dataset problem by a brain-neuron framework and an ensemble of a special type of artificial neural network (ANN) called fuzzy ARTMAP thereafter we applied a clustering algorithm known as fuzzy C-means clustering to handle missing value and also propose to make fuzzy ARTMAP cost-sensitive. Results indicate 100% accuracy in classification.

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1. INTRODUCTION

The theories of neural networks have witnessed multiple advancements in the computational intelligence field. Following the approaches implemented in the morphological development of neurons, we have obtained a well-defined model fuzzy ARTMAP (FAM) which is one of the artificial neural networks that is highly implemented in the areas of machine learning, deep learning, and data science. The modeling of human brain neurons requires the involvement of an imbalanced dataset. In this paper, the significance of multi-classed imbalanced datasets in the brain neuron model and how to do classification based on it is suggested. Fuzzy ARTMAP [1]-[5] is an architecture that incorporates fuzzy logic and the theory called adaptive resonance theory by utilizing a very minor similarity between computations of fuzzy subset hood, resonance, and learning.

A new brain-computer interface (BCI) design based on the notion of fuzzy ARTMAP was proposed by Palaniappan *et al.* [6]. This is a big-data era with enormous amount of data pouring in ranging from almost everywhere like telecommunication management [7]-[8], text classification [9], bioinformatics [10], medical data mining [11], direct marketing [12], oil spillage detection in satellite images [13], detection of weld flaws [14]. Also the literature study shows that the authors have proposed a neural network architecture for incremental supervised learning of analog multidimensional maps in [15], identification of DNA-binding proteins based on unbalanced classification in [16], financial sector, bioinformatics [17], pose-invariant face recognition [18], face detection and recognition [17]-[18] natural language understanding, selection for unbalanced class distribution and Naive Bayes method [19], document classification [20], information retrieval and filtering [21]-[22], critical value tables for evaluating classifiers [23] to name a few. Each application works on a voluminous amount of data. It has become difficult to handle such a voluminous amount of data. To classify an enormous amount of data is a big challenge in itself but whenever the data is imbalanced i.e., there is the existence of a majority class in which the instances of one class are very much greater than other classes and also a presence of an underrepresented class called the minority class. If there is a skewed representation of these classes, the classification of data becomes a very difficult problem. The problem is aggravated in presence of incomplete data, noise, and outliers. As many standard classification algorithms assume uniformity of the data representations they tend to fail in the presence of imbalanced big data where there is a bias for the majority class and all instances are classified to be accordingly belonging to the majority class and the other i.e., minority class is treated as noise.

In our quest to build intelligent systems we have but one naturally occurring model-the human brain. The human brain is the main precursor of artificial neural network (ANN) technologies. Here we put forward a new technique; we tried to give a new model for the classification of imbalanced data which is functionally based on Brain-neuron stimulation models and fuzzy ARTMAP. The brain is considered to use the imbalance in neurotransmitters, chemical ions, and hormones. We propose to classify data despite the existence of incomplete data, the presence of missing data, outliers, and noise. Instead of a single classifier, an ensemble of fuzzy ARTMAP approach is used for the classification of such unbalanced data. The layout of the research paper is as described below. In section 2 we describe related work, and a brief overview of and comparisons of some of the linked and connected works. Section 3 describes the framework of the brain-neuron classification model; section 4 describes the background details of fuzzy ARTMAP theory. Section 5 is concerned with the ensemble of FAM. and details the fuzzy-C means clustering algorithm. Section 6 is our proposed algorithm. Section 7 provides detailed and comparative experimentation on classification problems both with noise and without noise. The concluding remarks can be found in section 8.

2. RELATED WORK

By describing the geometrical perspective of fuzzy adaptive resonance theory in [2], the authors gave the two methodologies a new dimension. Ramentol *et al.* [5] propose a novel method based on an ordered weighted average for the closest neighbor approach and a fuzzy rough set for the classification of an unbalanced dataset. The Imbalanced dataset is categorized using a new algorithm methodology provided in this paper. There are four perspectives: data-level, algorithm-level, cost-sensitive, and ensemble methods. The six data-level approach-based methods are contrasted with the cutting-edge method IFROWANN in the unbalanced dataset, which has grown to be the gold standard for data pre-processing. Uncertainty sampling approaches iteratively request class labels for training cases whose classes are unknown despite the previously labeled instances were proposed by the authors in [9]. These techniques can significantly minimize the number of situations that require expert labelling. The author introduced grid cells and place cells in [24], along with their significance in brain-computer interaction and cognition. An adaptive space representation model based on grid cells and place cells inspired by the brain is mentioned in [24].

In Tan and Lim [25] the authors present fuzzy ARTMAP and hybrid evolutionary programming. The authors employed a FAM and hybrid evolutionary programming algorithm (FAM HEP) to categorize data in [26], where they addressed fuzzy ARTMAP with relevance factor. Tan *et al.* [27] proposes a fuzzy ARTMAP with dynamic decay adjustment, an improved fuzzy ARTMAP model with a conflict resolving facility. The authors created the dual vigilance adaptive resonance theory in [28]. For the optimal combination of variables, a multi-objective genetic algorithm is utilized, and then another GA is performed on the population of alternative solutions, selecting the best combination of FAM classifiers to build an ensemble of FAM as in [29]. Two vigilance values are used in the dual vigilance adaptive resonance theory in [30]. One is more rigid (data compression), whereas the other is more flexible (cluster similarity). The categories are mapped to the clusters using vigilance values. Generic ART networks can only capture clusters with internal category representations, but dual vigilance fuzzy ART can incarcerate clusters with random geometry. Parsapoor [31], a fuzzy integral method is used to combine various classifiers as an efficient technique. A hybrid parallel computing method for large geographical modelling problems is used in [32]. Because it is appropriate for extremely parallel and high-performance computing, an ensemble of fuzzy ARTMAP is used.

3. RESEARCH METHOD

3.1. A classification framework for the brain-neuron model

Many long processes called neurites are exhibited by brain cells or neurons. The receivers of the most contacts at synapses from the axons of other neurons are the remaining neurites and there are the branches called dendrites. The effect of the complex neuronal architecture on signal integration is influenced by the electrical signaling features of neurons.

Stimulus-reaction mechanism and target finding by axon is the aim of the brain-neuron model. We look at brain-neuron models of 4 types- neurite initiation, neurite elongation, axon pathfinding, neurite branching, and dendrite shape formation. We explain the construction of rules in the basic framework of neurite formation and these rules are used in the classification of any of the imbalanced datasets. Similarly, other algorithms based on neuron morphological stimulation are constructed for neurite elongation, axon path finding and dendrite shape formation. If-then rules are formed similarly. This procedure is not repeated here but rules are generated similarly.

3.2. Basic algorithm structure

In the context of the data classification problem, the proposed brain-neuron framework is introduced. Algorithm 1 is depicted schematically below. Let ξ and μ be the minimum and maximum values of all the parameters and there is the presence of two classes i. e. Na+ and Ca+ ions (minority class) and other ions (majority class).

```
Algorithm 1: - Neurite's formation.
Input: set of neuronal cells and parameters Si, Xi, Ti, D, A, V0, F, α, G, N, P.
Output: the set of axons, dendrites
Method:
    1. Initialize spherical neuronal cells S[m] population. S[m]=0
    2. Set the min and max values of all the parameters.
    3. Neurite initiation and differentiation:
    4. After initiation there is a differentiation process due to an imbalance of growth-
       permitting chemicals.
    5. (There is an imbalanced dataset i.e., minority class P is growth-permitting chemicals
       calcium ions, sodium ions, majority class -N is other ions in the brain cells).
    6. Special case: While P > N {there is an imbalance in ions concentration}
    7. Bulge in Cell body += {Na+ ions /Ca+ ions}
    8. This models the growth of axon which is an arbitrary long branch in the neurons.
```

If the neurite is excitable, sodium and calcium ions affect the local membrane potentials (minority class sodium and calcium ions, majority class other ions) via voltage-dependent sodium ions. Voltage-dependent channels can also mediate calcium influx. Focal depolarization is caused by a small bulge on the cell surface, which results in increased calcium and sodium entry and bulge calcium outgrowth, both of which result in neurite production. An unexplained chemical imbalance at the neurite tip is thought to slow neurite outgrowth. Diffusion carried this substance to the neurite end of the cell body. To model this, a set of equations representing the concentration of chemicals in the cell body was used. The concentration of chemicals in the cell body is x0, the chemical concentration in each neurite terminal is x1 to xn, and the lengths of each neurite are t1 to tn. The formulas are (1)-(4):

$$\mathrm{Ti} = \mathrm{DA}\frac{x0-x1}{ti} + \mathrm{F}\ \frac{dti}{dt}\,\mathrm{x0} \tag{1}$$

$$\frac{dx0}{dt} = \frac{1}{v0}\ \left[S - \sum_{i=1}^{n} Ti\right] \tag{2}$$

$$\frac{dxi}{dt} = \frac{1}{vi}\left[Ti - G\,\frac{dti}{dt}\right] \tag{3}$$

$$\frac{dti}{dt} = \alpha \mathrm{xi} \tag{4}$$

where A denotes a neurite's cross-sectional area, D denotes the diffusion constant, and Ti denotes the rate at which chemicals are transported from the soma to the neurite tip. The volume of soma is Vo, the neurite tip volume is vi, and the growth-relevant active transport rate is the rate of elongation of a growing neurite is proportional to its concentration in the tip- xi's, and consumption of chemicals is at a rate proportional to (G) the rate of elongation in the tip. If one neurite grows faster than the others, it develops into an axon, while the remaining neurites develop slowly.

This is because a 'winner-take-all' dynamic instability has emerged. We construct Table 1. Consider a table of hypothetical instances that will be used in the classification problem. In the form of this table, the parameters of the brain-neuron model can be mapped to the classification framework. The brain model contains 11 parameters that we considered for neurite elongation. These parameters are discussed in greater detail above. Let's try some different values for these parameters. In this case, the parameters are given arbitrary values to create an imbalance in the Ca^+ ions or Na^+ ions resulting in the formation of axon. This table is Table 1 a sample table for the formation of axon in brain-neuron model. IF-THEN-ELSE RULES formed for the classification of brain-neuron parameters. Similar classification rules can be formed for any of the imbalanced dataset from the UCI repository and mappings to classes can be generated in similar fashion If then else rules:

a) If 1.0 is ≤ A≤3.0 then Class X else if A ≤ 4.3 then Class Y else 0.6≤A≤5.6 then Class Z.
b) If 1.9≤B≤3.4 then Class X. If 2.3≤B≤5.6 then Class Y. If 3.4≤B≤6.2 then Class Z.
c) If 1.2≤C≤5.3 then Class X. If 3.4≤C≤ 6.3 then Class Y. If 2.3≤C≤6.7 then Class Z.
d) If 2.3≤D≤ 6.2 then Class X. If 3.4≤D≤5.6 then Class Y. If 2.3≤D≤4.3 then Class Z.
e) If 3.2≤ E ≤ 4.5 then Class X. If 3.4 ≤ E≤6.2 then Class Y. If 2.3≤ E≤5.3 then Class Z.

f) If 3.4≤F≤ 5.4 then Class X. If 2.3≤F≤6.7 then Class Y. If 2.3≤F≤ 6.9 then Class Z.
g) If 1.2≤G≤ 5.2 then Class X. If 2.3≤G≤6.8 then Class Y. If 2.0≤G≤ 6.3 then Class Z.
h) If 2.0≤H≤ 4.5 then Class X. If 1.9≤H≤6.7 then Class Y. If 0.5≤H≤ 5.4 then Class Z.
i) If 3.4≤I≤ 6.3 then Class X. If 3.2≤I≤5.2 then Class Y. If 3.2≤I≤5.7 then Class Z.

Table1 describes the sample table for the formation of axon in brain-neuron model. Brain-neuron algorithm which is proposed here is applied for the classification of the artificially created Imbalanced Iris flower dataset. We have taken this dataset from the learning repository of UCI machine learning. In Table 2 shows the min and max of the values and mapping to 3 classes can be identified.

Table 1. Sample table for the formation of axon in brain-neuron model

Classes C	Si A	Xi B	Ti C	D D	A E	V0 F	F G	α H	G I	N/P	Axon
X	1.0	2.3	3.4	5.6	3.2	5.4	4.3	2.0	5.3	1.0	Y
X	1.2	3.4	5.3	6.2	4.3	4.2	5.2	2.9	6.3	1.0	Y
X	1.5	2.3	3.3	4.3	4.5	3.4	1.2	3.3	3.4	1.0	Y
X	2.4	1.9	4.5	2.3	4.3	3.6	2.3	4.5	5.6	1.0	Y
X	3.0	3.4	1.2	4.5	4.5	3.4	4.5	4.3	5.7	1.0	Y
Y	4.3	4.5	5.4	4.2	5.6	2.3	6.8	3.6	3.2	0.0	N
Y	3.6	5.6	4.2	5.6	5.6	2.3	6.8	3.6	3.2	0.0	N
Y	2.2	3.2	3.4	4.5	3.4	4.5	3.4	6.7	4.2	0.0	N
Y	1.0	2.3	3.3	4.2	6.2	4.2	3.2	1.9	4.2	0.0	N
Y	3.7	3.5	6.3	3.4	5.6	2.3	6.8	3.6	3.2	0.0	N
Z	0.6	3.4	4.2	3.7	5.3	4.2	2.0	0.5	5.7	1.0	Y
Z	4.5	5.2	6.7	3.5	2.3	2.3	4.5	5.4	4.3	1.0	Y
Z	3.2	3.4	4.5	2.3	4.5	3.4	5.6	3.4	3.2	1.0	Y
Z	5.6	6.2	5.6	4.3	3.4	4.5	6.3	5.3	4.2	1.0	Y
Z	4.3	4.3	2.3	3.2	4.5	6.9	3.4	4.2	4.2	1.0	Y

Table 2. The normalization step after completion of steps in Table 1

C	Si A min	max	Xi B min	max	Ti C min	max	D D min	max	A E min	max	V0 F min	max	F G min	max	A H min	max	G I min	max
X	1.0	3.0	1.9	3.4	1.2	5.3	2.3	6.2	3.2	4.5	3.4	5.4	1.2	5.2	2.0	4.5	3.4	6.3
Y	1.0	4.3	2.3	5.6	3.4	6.3	3.4	5.6	3.4	6.2	2.3	6.7	2.3	6.8	1.9	6.7	3.2	5.2
Z	0.6	5.6	3.4	6.2	2.3	6.7	2.3	4.3	2.3	5.3	2.3	6.9	2.0	6.3	0.5	5.4	3.2	5.7

3.2. Iris dataset

50 samples were taken from each of the three species of Iris flowers from Iris dataset. Specifically, Iris Setosa, Iris Virginica, and Iris Versicolor. Each sample is evaluated with the help of four characteristics: sepal length (SL), sepal width (SW), petal length (PL), and petal width (PW). We have artificially made the Iris dataset highly Imbalanced. From the data taken from the UCI repository and from observations of the value of the species of flower and their characteristics, it is clear that the petal width (PW) is the most significant attribute for classification. This is due to the use only for petal width ranging from 1.4 to 1.8, the classification is ambiguous, whereas, for other petal width values, the classification can be explicitly classified. As a result, according to the brain-neuron framework.

1. If the PW is 1.9 to 2.5 then Class Virginica.
2. If the PW is 0.1 to 0.6 then Class Setosa.
3. If the PW is 1.0 to 1.3 then Class Versicolor.
4. If the PW is 1.6 and the SL is 7.2 or the SW is 3.0 or the PL is 5.8 then Class Virginia otherwise Class Versicolor.
5. If the PW is 1.4 and the SW is 2.6 or the PL is 5.6 then Class Virginica otherwise Class Versicolor.
6. If the PW≤ 1.7 and the SL≤ 4.9 or the SW ≤ 2.5 orPL≤ 4.5 then Class Virginica otherwise Class Versicolor.
7. If the PW≤ 1.5 and the PL≥5.0 then Class Virginica otherwise Class Versicolor.
8. If the PW≤ 1.8 and the SL≤5.9 and the SW ≤ 3.2 and the PL ≤ 4.8 then Class Versicolor otherwise Class Virginica.

4. FUZZY ARTMAP

ANN are commonly used to represent the brain. The artificial neural network is commonly used in classification and pattern recognition. But, the generalization capabilities of classic neural networks are limited, resulting in overfitting in training samples. Fuzzy ARTMAP (FAM) is an incremental and supervised model based on adaptive resonance theory that can solve the plasticity-stability conundrum, i.e., how can a learning system protect historical data. However, when a single FAM is applied to the classification fields, the classification accuracy is not very good due to the FAM's limitations, such as the effect of sample presentation order for offline training. So, we propose an ensemble of FAM which overcomes many of these problems and gives a better classification. Each module in FAM is comprised of 3 layers. Normalization layer F_0, input layer F_1, and recognition layer F_2. The structure of FAM is shown in the Figure 1. When the output domain is a set of finite class labels, FAM can be utilized as the classifier. We do not consider output from a single classifier but an ensemble of multiple classifiers is built as in [29]. The combination method for ensemble that is used is Voting method. Algorithms 2 and 3 are as follows.

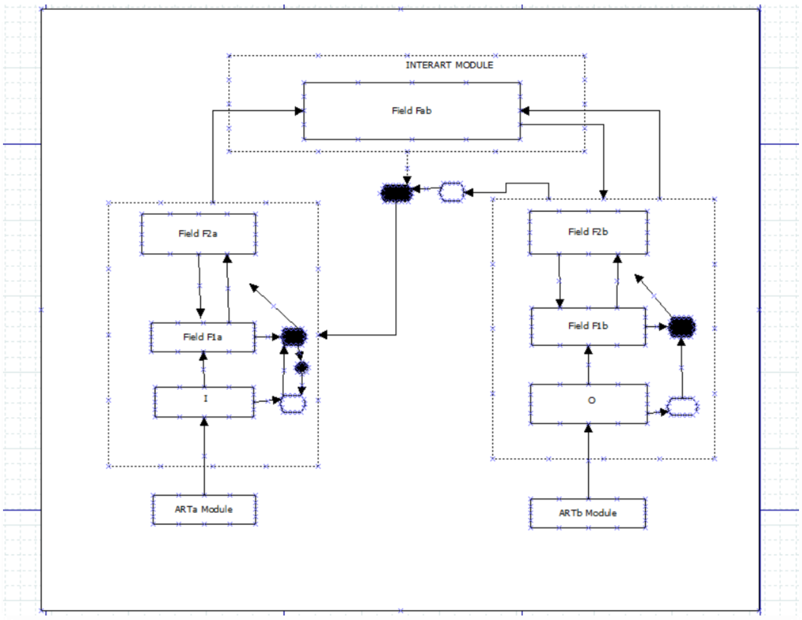

Figure 1. A fuzzy ARTMAP

```
Algorithm 2
Procedure Imbalanced_Dataset
{ {
Initialize target_class
Set λ, µ
Call function evolution
Call Procedure
Imbalanced_Dataset
While (target_class <  λ )
{
{
Select the row of each class
If(β_class_weight=F1_score)
then
{
β_class_weight=2*(precision*
recall)/
    precision + recall
}
}
Rank target_class based on
fitness
Get the best solution}}
 Procedure
Imbalanced_Dataset
{
Intialize data
set=Evaluation_metric
With fitness resulting from
actual evolution
While (target_class > λ )
{
Select β_class_weight
If(β_class_weight=penaltyFunction)
then
{
 Change the evaluation Metric
Rank target_class based on Fitness
Get the best solution
}
}
/*This procedure selects the most
likely model for each class*/
Procedure Majority_class
{
While (target_class <=λ &&
target_class>= µ)
{
Determine the degree of Imbalance in
the given test sample
}}}

Algorithm 3
Procedure Fuzzy ARTMAP
{
Initialize penaltyFunction1
Set Minority and Majority
While(Majority >penaltyFunction1){
Continue
}
Else if(Minority <penaltyFunction1){
Minority=Minority * penaltyFunction1
}}}
While(Majority<= penaltyFunction1){
Majority=Majority*penaltyFunction1
}}
}}
Intialize
penaltyFunction2
Set Minority and
Majority
While(Minority<=pena
ltyFunction2){
Continue
}
Else if(Majority
>penaltyFunction2)
}}
While(Minority >
penaltyFunction2){

Minority=Minority*pe
naltyFunction2
}
}
Procedure
FuzzyARTMAP
{
Intialize
penaltyFunction1 and
penaltyFunction2
If (penaltyFunction1
or
penaltyFunction2){
Do classification}
}
```

5. AN ENSEMBLE OF FUZZY ARTMAP

This normalization is taken up to prevent the category drift and propagation problem. This preprocessing step is realized at the F_a^0/F_b^0 layer. After preprocessing the input pattern is propagated from F_a^1/F_b^1 to F_a^2 through a set of flexible weights. Given an input from F_a^1, the activation node is defined by a choice function Tj(I) as [1]. The vigilance test and entropy is also calculated as given in [1]. The fuzzy C-Means clustering algorithm is applied to ensemble of fuzzy ARTMAPS and the 3 methods are proposed to solve the missing value problem from it as given in [29]. These methods are partial distance strategy (PDS), optimal completion, and the ensemble result can be further improved. Some of the classes on the boundary of the decision region are considered noise. They differ from minority classes as they may contain incomplete information or null values and they do not form the part of the decision region. Sensitiveness to input order matters in fuzzy ARTMAP and some of the classes may be overlapping so the noise had to be removed by using some newfound technique. The entropy calculated as defined earlier after the vigilance test confirms the accuracy of the categories which is 100% as the vigilance test can be fine-tuned by cost component. We compared the various ensemble methods for class imbalance learning (CIL) with our brain-neuron method. We have chosen 10 datasets from the machine learning UCI repository. These are abalone (Abaone), Balanced (Balan), cmc (cmc), Haberman (Haber), Housing (Hous), mf-morph (Mfm), mf-zernike (Mfz), pima (pima), Vehicle (Vehic), wpbc (Wpbc) as given in Table 3. The methods in comparison are as given in Table 3. For fair comparison, all methods are ensemble methods, and they use AdaBoost or CART as base algorithm. These methods are comprised into 3 groups. Standard ensemble methods (group I) CIL and Bagging style method for CIL. Table 3 shows different methods in comparison. Table 4 shows AUC results of various methods in discussion. Figure 2 shows the comparison between the OCS and NPS methods with varying percentages of missing features in the training set. Figure 3 shows the overall accuracy rates of OCS and NPS method subject to varying percentages of missing features in the training and test data sets.

Table 3. The methods in comparison

	Methods	Type
Group1	1.Bagging	Standard Ensemble Method
	2.AdaBoost	Standard Ensemble Method
	3.Random Forest	Standard Ensemble Method
Group2	4.Under-sampling+AdaBoost	CIL Method
	5.Under-sampling +Random Forests	CIL Method
	6.Over-sampling+AdaBoost	CIL Method
	7.Over-sampling+Random Forests	CIL Method
	8.SMOTE+under-sampling+AdaBoost	CIL Method
Group3	9.Chan+AdaBoost Balanced	Bagging style Method for CIL
	10.Balanced Random Forests	Bagging style Method for CIL
	11.AsymBoost	Boosting based method for CIL
	12.SMOTEBoost	Boosting based method for CIL
	13.EasyEnsemble	Hybrid ensemble for CIL
	14.BalanceCascade	Hybrid ensemble for CIL

Table 4. AUC results

	Abalone.	Balan.	Cmc.	Haber.	Hous.	Mfm.	Mfz.	Pima.	Vehic.	Wpbc.	Avg
Bagg	0.824	0.439	0.705	0.669	0.825	0.887	0.855	0.821	0.859	0.688	0.757
Ada	0.811	0.616	0.675	0.641	0.815	0.888	0.795	0.788	0.854	0.716	0.760
RF	0.827	0.435	0.669	0.645	0.828	0.880	0.840	0.821	0.869	0.677	0.749
Under-Ada	0.830	0.617	0.671	0.646	0.805	0.916	0.881	0.789	0.846	0.694	0.769
Under- RF	0.842	0.593	0.676	0.643	0.820	0.919	0.889	0.818	0.855	0.661	0.772
Over-Ada	0.817	0.540	0.675	0.637	0.821	0.889	0.779	0.791	0.855	0.711	0.751
Over-RF	0.823	0.458	0.660	0.641	0.826	0.881	0.854	0.819	0.866	0.670	0.750
Smote	0.831	0.617	0.680	0.647	0.816	0.912	0.862	0.792	0.858	0.709	0.772
Chan	0.850	0.652	0.696	0.638	0.811	0.912	0.903	0.786	0.856	0.706	0.781
BRF	0.853	0.558	0.683	0.677	0.798	0.901	0.866	0.809	0.850	0.646	0.764
Asym	0.812	0.619	0.675	0.639	0.815	0.888	0.801	0.788	0.853	0.721	0.761
SMB	0.818	0.599	0.687	0.646	0.824	0.897	0.788	0.790	0.864	0.720	0.763
Easy	0.847	0.633	0.704	0.668	0.825	0.918	0.904	0.809	0.859	0.707	0.787
Cascade	0.828	0.637	0.686	0.653	0.808	0.905	0.891	0.799	0.856	0.712	0.778
Brain-Neuron	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

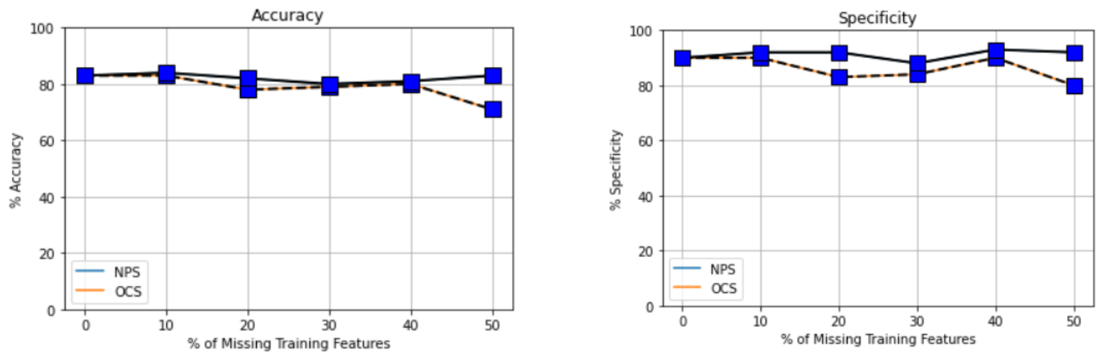

Figure 2. Comparison between the OCS and NPS methods with varying percentages of missing features in the training set

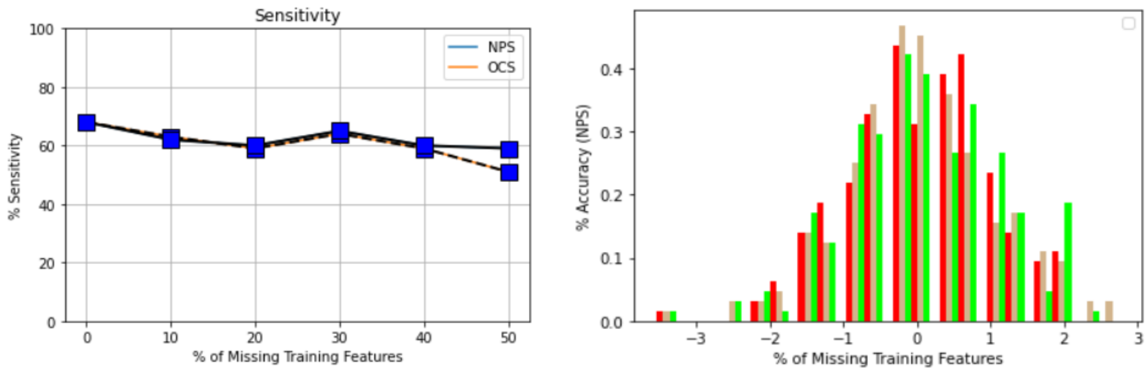

Figure 3. The overall accuracy rates of OCS and NPS method subject to varying percentages of missing features in the training and test data sets

6. CONCLUSION

The ensemble of fuzzy ARTMAP, as it occurs in brain-neuron classification framework. is used to solve the imbalanced dataset problem. The incomplete information in the datasets is also solved using fuzzy C-Means clustering. The process is tested on Iris Dataset and shows 100% accuracy. The if-then rules formed are used to classify datasets based on the brain neuron model. The future scope of this paper is in creating Brain-computer Interface so that 100% accurately classified data can be further used.

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