Classification Of Brain Disorder Images Using Fractal Based Machine Intelligence Approach

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Abstract:

Brain Disorder (BD) is considered as a major concern for the entire human society. It can destroy the thinking skills and memory of human beings. So, it is very much essential for the early classification of BD images (BDIs) into several categories so that preventive measures can be taken accordingly at the earliest. In this work, a fractal based machine intelligent (MI) based approach is proposed for the classification of BDIs into several categories such as Atrofi (AF), Bci (BC), Iskemi (IK) and normal (NR) types. The proposed approach is focused on the stacking (hybridization) of Logistic Regression (LRG) and Neural Network (NNT) methods to carry out such classification. The proposed method is compared with other machine learning (ML) based methods such as AdaBoost (ADB), Random Forest (RFS), Decision Tree (DTR), K-Nearest Neighbor (KNNH), Support Vector Machine (SVMN), LRG and NNT for performance analysis.

The proposed method and other ML based methods have been implemented using Python based Orange 3.26.0. In this work, 444 BDIs having 100, 92, 102 and 150 numbers of AF, BC, IK and NR type each are taken from the Kaggle source. The performance of all the methods is assessed using the performance parameters such as classification accuracy (CA), F1, Precision (PR) and Recall (RC). From the results, it is found that the proposed method is capable of providing better classification results in terms of CA, F1, PR and RC as compared to other ML based methods such as ADB, RF, DTR, KNNH, SVMN, LRG and NNT.

Keywords: Brain Disorder Images, Machine Intelligence, Classification Accuracy, F1, Precision, Recall

DOI Number: 10.14704/nq.2022.20.9.NQ440084 **Neuro Quantology 2022; 20(9):750-756**

1. INTRODUCTION

BD [1-28] is recognized as a major concern for the entire human society in the current scenario. It can able to destroy the thinking skills and memory of human beings. So, it is very much essential for the early classification of BDIs into several categories such as AF, BC, IK, NR, etc., so that preventive measures can be taken accordingly at the earliest.

ML [1-29] can be considered as a solution for the classification of BDIs into several categories. The ML based methods can be broadly classified as supervised and unsupervised. The Supervised ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, etc. play a significant role to accomplish the classification mechanism. However, each ML based method is not capable of providing better classification results in several situations. The performance of each ML based method varies from one scenario to another scenario. So, it is a very challenging task to perform the classification mechanism accurately in different scenarios. Therefore, there is a need for some enhanced methods to carry out the categorization mechanism in a better way. In this work, the main focus is given to the classification of BDIs into several categories such as AF, BC, IK and NR [30] in a better way. Here, a MI [1-29] based approach is

proposed to carry out the classification of BDIs into several types. This approach is focused on the stacking of LRG and NNT methods to carry out such classification. The proposed method is able to perform better in terms of CA, F1, PR and RC than ADB, RFS, DTR, KNNH, SVMN, LRG and NNT methods. Here, the proposed work tries to provide better classification results than other methods.

The contributions in this work are mentioned as follows.

- In this work, a fractal based MI based approach is proposed for the classification of BDIs into AF, BC, IK and NR types.
- The proposed approach is focused on the stacking of LRG and NNT methods to carry out such classification mechanisms.
- The proposed method is compared with other ML based methods such as ADB, RFS, DTR, KNNH, SVMN, LRG and NNT in terms of CA, F1, PR and RC for performance analysis.
- The Simulation of this work is accomplished using python based Orange 3.26.0.
- From the results, it is found that the proposed method is capable of providing better classification results than other ML based methods in this scenario.

The rest of this work is presented as follows. Section 2 to Section 5 describes the related works, methodology, results and discussion and conclusion respectively.

2. RELATED WORKS

Many research works have been accomplished related to the BDIs processing and analysis [1-28]. Some of the works are mentioned as follows. Zhang et al. [1] concentrated on the categorization of BD by focusing on diffusion kernel attention network. Du et al. [2] focused on the functional connectivity process for the categorization and prediction of BD. Li et al. [3] concentrated on the unified functional network target for the stimulation of deep brain by focusing on obsessive-compulsive disorder. Jiang et al. [4] focused on the analysis of facial expressions for the categorization of crucial depressive disorder as well as response to stimulation of deep brain. Shahid et al. [5] emphasized on the prediction of neuro-psychiatric disorders in brain tumors by focusing on ML based model. Nogay et al. [6] emphasized on the diagnosis of autism spectrum disorder using ML by focusing on brain imaging process. Das et al. [7] concentrated on the optimized extreme gradient boosting ensemble classifier for the categorization of brain image. Cremers et al. [8] focused on the brain network measures for the categorization of borderline personality dis-order during emotion regulation. Mikolas et al. [9] concentrated on the categorization of first episode schizophrenia spectrum disorders using ML based approach. Yin et al. [10] focused on the diagnosis of BD by focusing on deep learning based approach.

3. METHODOLOGY

In this work, a MI [1-29] based approach is proposed for the classification of BTMIs [30] into AF, BC, IK and NR types. The proposed approach is focused on the stacking of LRG and NNT methods to carry out such classification. The proposed method is compared with other ML based methods such as ADB, RFS, DTR, KNNH, SVMN, LRG and NNT in terms of CA, F1, PR and RC for performance analysis. The methodology is described in Fig. 1.

At first, the BTMIs are imported to Orange 3.26.0 [31] through the Import Images option. Afterwards, the image embedding (IED) process is accomplished on the BTMIs to extract the essential features such as height, width, etc. For IED, several embedders such as Squeeze-Net, Inception v3, DeepLoc, etc. can be used. In this work, SqueezeNet (local) embedder is considered for processing. After the completion of the IED process, test and score computation will be performed by considering the ML based methods such as ADB, RFS, DTR, KNNH, SVMN, LRG, NNT and the proposed method to find out the CA, F1, PR and RC values in units. The test and score computation can be performed by considering cross validation (COV) as well as random sampling mechanisms. In this work, the COV process is focused. The COV process can be carried out by recognizing the number of folds (NF) as 2, 3, 5, 10, 20, etc. But, in this work, the NF value is considered as 5 to accomplish the classification mechanism.

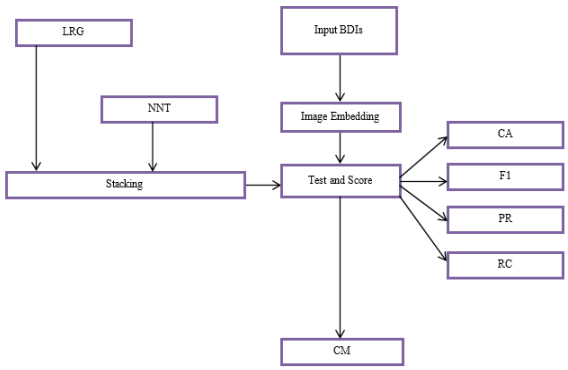

Fig. 1: Methodology

In this work, the parameter setup for each method is described as follows. For LRG, the regularization type can be considered as Lasso (L1) and Ridge (L2). İn this work, Ridge (L2) is considered for processing. The strength value (STV) for this work is considered as per equation (1).

$$STV=1 \quad (1)$$

For SVMN, the kernel can be considered as Linear, Polynomial, RBF and Sigmoid. In this work, the kernel is considered as a radial basis function and the iteration limit is taken as 100. Here, the numerical tolerance (NTC) value is taken for processing as per equation (2).

$$NTC=0.0010 \quad (2)$$

In this work, for RFS the number of trees (NTE) considered for processing is mentioned in equation (3).

$$NTE=50 \quad (3)$$

For NNT, the activation function can be considered as ReLu, Logistic, tanh, etc. The solver can be considered as Adam, SGDC, L-BFGS-B, etc. In this work, the activation function is considered as ReLu and the solver is considered as Adam with the maximal number of iterations as 100. The neurons (NU) in hidden layers and regularization (REG) value are considered in this work as per equation (4) and equation (5) respectively.

$$NU=200 \quad (4)$$

$$REG=0.0001 \quad (5)$$

For DTR, the maximum tree depth (MTDT) is considered as per equation (6) with the minimum number of instances in leaves as 4.

$$MTDT=100 \quad (6)$$

For KNNH, the metric can be considered as Euclidean, Manhattan, Chebyshev and Mahalanobis and the weight (WT) can be considered as distance (dis) and uniform (un). In this work, for KNNH weight value is mentioned in equation (7) by considering the number of neighbors as 10 and the metric as Manhattan. WT=dis (7)

At the test and score computation, the CA, F1, PR and RC values (in units) are computed. Then, the confusion matrix (CM) representation can be carried out. The CM can be represented by considering the number of instances, proportion of predicted and proportion of actual values. However, in this work, the number of instances is considered for processing. The methodology used in this work for the classifycation of BTMIs into AF, BC, IK and NR types is described in Algorithm 1.

Algorithm 1: BDI Classification
Input: BDIs
Output: AF, BC, IK and NR Type

Step 1: Start
Step 2: Input BDIs
Step 3: IED (BDIs)
Step 4: Test and Score (ADB, RFS, DTR, KNNH, SVMN, LRG, NNT , Proposed method)
Step 5: Compute CA, F1, PR and RC by applying ADB, RFS, DTR, KNNH, SVMN, LRG, NNT and the Proposed method
Step 6: Create (CM) for each method to analyze the classification results
Step 7: Stop

4. RESULTS AND DISCUSSION

The simulation of this work is accomplished using Python based Orange 3.26.0 [31]. In this work, 444
BDIs having 100, 92, 102 and 150 numbers of AF, BC, IK and NR type each are taken from the source [30].The Orange workflow setup diagram is mentioned in Fig. 2. The sample representation of AF, BC, IK and NR types are mentioned in Fig. 3 to Fig. 6 respectively. The BDIs are processed using several ML based methods such as ADB, RFS, DTR, KNNH, SVMN, LRG, NNT and the proposed method when the NF value is recognized as 5. The performance of all the methods is accessed using performance parameters such as CA, F1, PR and RC which are described as follows.

- **CA:** It refers to the rate of correct classification. It is represented in equation (8) by considering the number of corrected pre-dictions (CPD) and the total number of input samples (IS).

CA= CPD / IS (8)

- **F1:** It is the harmonic mean of PR and RC. It is mentioned in equation (9).

F1= 2* (PR * RC) / (PR + RC) (9)

- **PR:** It is represented in equation (10) by considering the true positives (TP) and false positives (FP).

PR= TP / (TP+FP) (10)

RC: It is represented in equation (11) by considering the TP and false negatives (FN).

RC= TP / (TP+FN) (11)

The classification results are better when the CA,F1, PR and RC values are higher. Table 1 describes the CA, F1, PR and RC computed values (in units) of the proposed method and other methods. Fig. 7 to Fig. 10 represents the comparison results of all methods graphically in terms of CA, F1, PR and RC respectively. This work is also focused on CM representation. The CM represents the actual and predicted values by showing the number of instances for each of these methods. The CM representation for ADB, RFS, DTR, KNNH, SVMN, LRG, NNT and the Proposed method are mentioned in Fig. 11 to Fig. 18 respectively. In CM, the actual values are represented using light blue color and the predicted values are represented using light pink color.

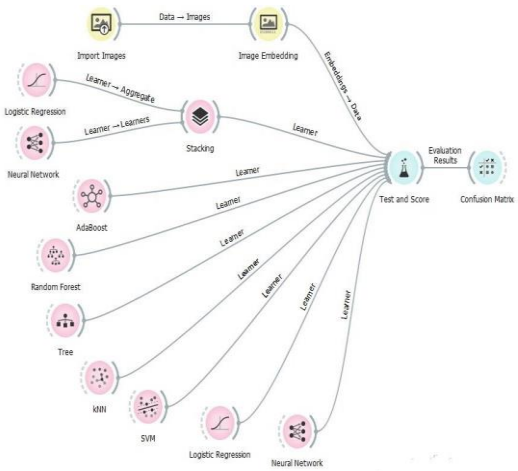

Fig. 2: Orange workflow setup diagram

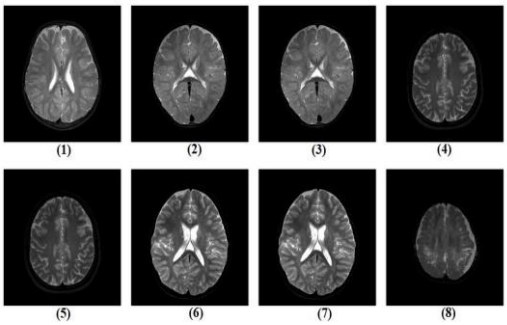

Fig. 3: Sample depiction of AF type

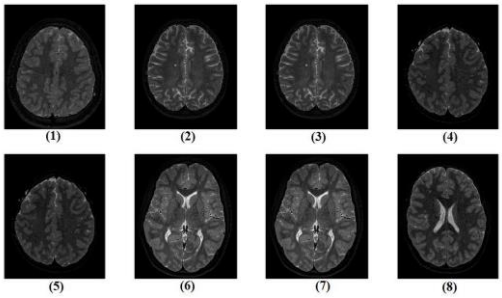

Fig. 4: Sample depiction of BC type

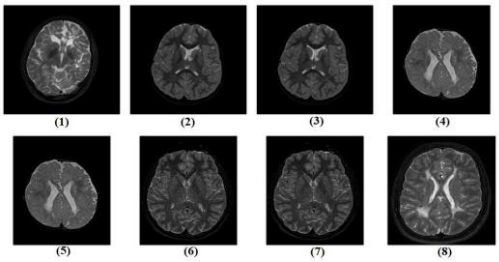

Fig. 5: Sample depiction of IK type

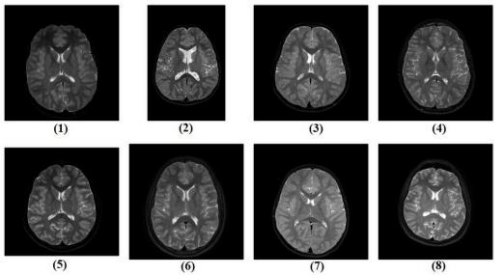

Fig. 6: Sample depiction of NR type

Table 1: Comparison of the proposed method with other MI based methods

Method	CA	F1	PR	RC
ADB	0.800	0.800	0.803	0.800
RFS	0.608	0.591	0.613	0.608
DTR	0.685	0.679	0.692	0.685
KNNH	0.806	0.807	0.809	0.806
SVMN	0.669	0.657	0.753	0.669
LRG	0.827	0.826	0.831	0.827
NNT	0.822	0.823	0.825	0.822
Proposed Method	0.840	0.840	0.841	0.840

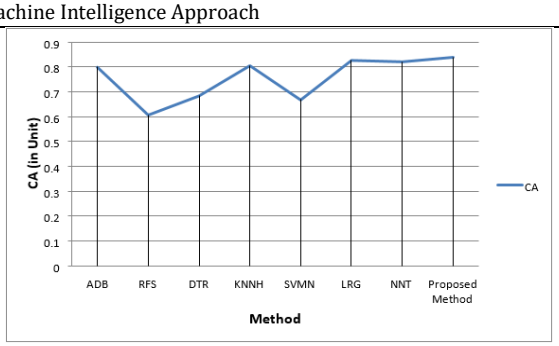

Fig. 7: Comparison results representation of all methods in terms of CA

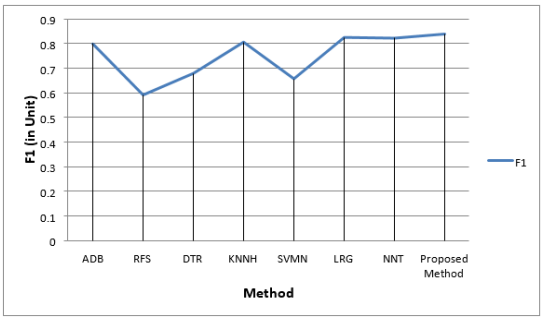

Fig. 8: Comparison results representation of all methods in terms of F1

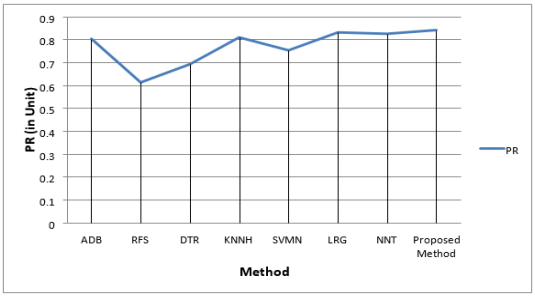

Fig. 9: Comparison results representation of all methods in terms of PR

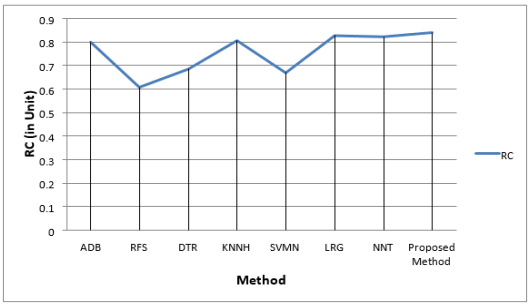

Fig. 10: Comparison results representation of all methods in terms of RC

Fig. 11: CM of ADB

Fig. 12: CM of RFS

Fig. 13: CM of DTR

Fig. 14: CM of KNNH

Fig. 15: CM of SVMN

Fig. 16: CM of LRG

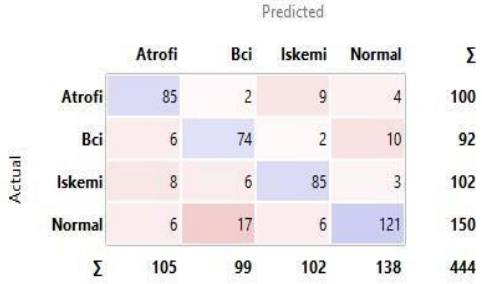

Fig. 17: CM of NNT

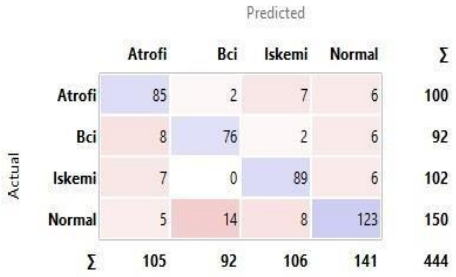

Fig. 18: CM of Proposed Method

From Table 1 and Fig. 7 to Fig. 18, it is observed that ADB, RFS, DTR, KNNH, SVMN, LRG, NNT and the Proposed method are able to provide 0.800, 0608, 0.685, 0.806, 0.669, 0.827, 0.822 and 0.840 CA values (in unit) respectively. ADB, RFS, DTR, KNNH, SVMN, LRG, NNT and the Proposed method are able to provide 0.800, 0591, 0.679, 0.807, 0.657, 0.826, 0.823 and 0.840 F1 values (in unit) respectively. ADB, RFS, DTR, KNNH, SVMN, LRG, NNT and the Proposed method are able to provide 0.80, 0613, 0.692, 0.809, 0.753, 0.831, 0.825 and 0.841 PR values (in unit) respectively. ADB, RFS, 3DTR, KNNH, SVMN, LRG, NNT and the Proposed method are able to provide 0.800, 0608, 0.685, 0.806, 0.669, 0.827, 0.822 and 0.840 RC values (in unit) respectively. So, the proposed method is capable of providing better classification results as compared to ADB, RFS, DTR, KNNH, SVMN, LRG and NNT methods and it is having 0.840, 0.840, 0.841 and 0.840 CA, F1, PR and RC values in units respectively. However, the RFS method is not capable of providing better categorization results than other methods and it is having 0.608, 0.591, 0.613 and 0.608 CA, F1, PR and RC values in units respectively. The decreasing order of performance of these methods is proposed method, LRG, NNT, KNNH, ADB, DTR, SVMN, ADB and RFS.

5. CONCLUSION

This paper proposed a fractal MI based approach for the classification of BDIs into AF, BC, IK and NR types. The proposed approach is focused on the stacking of LRG and NNT methods to carry out the classification of BDIs into such categories. From the results, it is found that the proposed method is capable of providing better classification results in terms of CA, F1, PR and RC as compared to other ML based methods such as ADB, RFS, DTR, KNNH, SVMN, LRG and NNT. The CA, F1, PR and RC values in units using the proposed method are computed as 0.840, 0.840, 0.841 and 0.840 respectively which is higher as compared to other methods. However, in this scenario, the RFS method is unable to perform better than other methods. The CA, F1, PR and RC values in units using the RFS method are computed as 0.608, 0.591, 0.613 and 0.608 respectively which are lower than other methods in this scenario. This approach can help the researchers to carry out the image classification mechanism in a better way for several applications. This work can be extended to develop improved methods to carry out the classification of BDIs and other types of images in terms of higher CA, F1, PR and RC. This work can also be extended to process and analyze the classification results of BDIs and other types of images by applying other MI based methods.

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