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An Algorithm for Determination of Rank and Degree of Contribution of sMRI Volumetric Features in Depression Detection

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Abstract— **Brain volume changes at structural level appear to have utmost importance in depression biomarkers studies. However, these brain volumetric findings have very minimal utilization in depression detection studies at individual level. Thus, this paper presents an evaluation of volumetric features to identify the relevant/optimal features for the detection of depression. An algorithm is presented for determination of rank and degree of contribution (DoC) of structural magnetic resonance imaging (sMRI) volumetric features. The algorithm is based on the frequencies of each feature contribution toward the desired accuracy limit. Forty-four volumetric features from various brain regions were adopted for evaluation. From DoC analysis, the DoC of each volumetric feature for depression detection is calculated and the features that dominate the contribution are determined.**

I. Introduction

Depression is the most common mental disorder worldwide, and currently the fourth largest contributor to the burden of disease as reported by the World Health Organization [1]. It is estimated that by 2020, depression will remain a leading cause of disability, second only to cardiovascular disease [1]. Approximately 121 million people worldwide have been affected by depression [2]. Depression is associated with widely varying psychological and physiological features, and this heterogeneity is acknowledged within classification systems [3].

Diagnostic criteria for major depressive disorder (MDD) are currently based on clinical and psychometric assessment. Some widely used screening tests for the evaluation of depression include the Hamilton Rating Scale for Depression, Diagnostic Interview Schedule and Hospital Anxiety and Depression Scale.

In this paper, the brain structural MRI (sMRI) volumetric features are investigated to determine the most important features that contribute towards more accurate depression detection, whether a person is in depressed or non-depressed forms. The 3-D volumetric features are extracted from sMRI data provided by Neuropsychiatric Imaging Research Laboratory at Duke University named as Multisite Imaging Research In the Analysis of Depression (MIRIAD) [4]. To authors' knowledge, this is the first study that exploring the feature selection for depression classification from volume of multiple brain regions. The contributions of this paper include: (i) introduction of a new algorithm for determination of DoC of sMRI volumetric features, and (ii) evaluation and determination of the most discriminant sMRI volumetric features for single-subject classification of depression using the proposed algorithm.

This paper is organized as follows. Section II describes the related background. Section III presents the proposed algorithm. Section IV gives the experimental procedures. Section V presents the experimental results. Section VI provides discussion of the results. Finally, conclusions are given in Section VII.

II. Background

Feature selection identifies the most useful features, and reduces the dimensionality whilst the most significant aspects of the data are represented by the selected features [5]. Feature selection can be summarized into three categories: filter, wrapper, and hybrid methods. The limitations of ranking and subset selection approaches clearly suggest that a hybrid model should be pursued [6]. In this this paper, we propose DoC which facilitates feature selection by ranking results and total frequency distribution, and applies it to the final selection process.

Feature ranking also called feature weighting, assesses individual features and assigns to them weights according to their degrees of relevance, while the feature selection (FS) evaluates the goodness of each found feature subset [6]. We considered FS methods as experts giving opinion on the ranking of the features. Each FS algorithm used has a different way of mathematical calculation thus has its own advantages and disadvantages.

sMRI is a widely available [7] and widely used neuroimaging technique in research as well as clinical practice [8]. Previous neuroimaging studies that used sMRI of depression patients reported certain patterns of brain changes that may be present at a structural levels [5]. Specifically, the image-based volumetric analysis of brain regions has drawn a lot of attention in depression related research in the past decade [5]. In depression detection, volumetric studies have identified reductions or increase in the hippocampus, amygdala, anterior cingulate cortex, orbitofrontal cortex, dorsolateral prefrontal cortex, subgenual prefrontal cortex, putamen, caudate and also cerebrospinal fluid. Therefore, there is a need to investigate the most relevant features for depression detection [5].

To date, there are several individual depression detection studies based on sMRI (Costafreda et al.[9], Nouretdinov et al. [10], Gong et al. [11], Mwangi et al. [12, 13], Bao et al.

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[14]). However, it is noticed that feature selection processes still have not gained much attention. There are only few studies that report on feature selection process. Costafreda et al. [9] implemented the whole-brain analysis of variance filtering to select the areas of maximum group differences between patients and controls. Mwangi et al. [12] implemented a feature selection *t*-test filter in VBM to identify the voxels that differed most in MDD patients versus healthy controls. They also investigated a wrapper feature selection method called Recursive Feature Elimination.

III. Proposed Algorithm

A. Formulation of Degree of Contribution (DoC)

Inspired by the approach in [15], we propose a DoC calculation algorithm in order to determine feature ranking and also associate importance level to them. The DoC rules are mainly based on the accuracy achieved by each feature. The algorithm is proposed in order to evaluate the power of each feature and assist FSS. The derivation of DoC is based on the circle mechanism shown in Fig. 1.

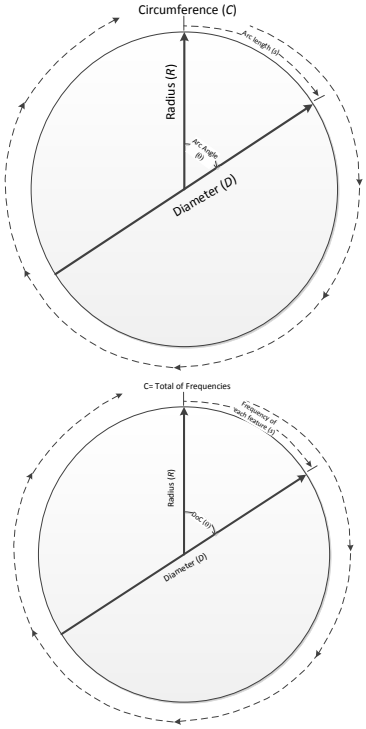

Figure 1. Representation of Degree of Contribution (DoC) based on the circle method.

The total frequency of all features is:

$$Tf = \sum_{k=1}^{n} f_{F_k} \quad (1)$$

where f_{F_k} is the frequency for *k*th feature (F_k) defined as:

$$f_{F_k} = ArcLength(s_k) \quad (2)$$

where s_k is the length of the curve on the circumference of the circle associated with f_{F_k}. The Radius (R) of the circle therefore is:

$$R = \frac{\sum_{k=1}^{n} f_{F_k}}{2\pi} \quad (3)$$

The generic formula of the arc angle is:

$$Arc\ Angle\ (^\circ) = (Arch\ length(s)/radius(R)) \times (180/\pi) \quad (4)$$

The DoC of the *k*th feature (F_k) is therefore:

$$DOC_{F_k} = f_{F_k} \times \frac{2\pi}{\sum_{k=1}^{n} f_{F_k}} \times \frac{180}{\pi} = \frac{f_{F_k}}{\sum_{k=1}^{n} f_{F_k}} \times 360 \quad (5)$$

The DOC represents the contribution of the feature, the higher the degree the more important the feature.

ALGORITHM: The algorithm for determination of the degree of contribution of sMRI volumetric features for depression detection involves a number of steps as follows:

1) Volumetric features are selected (see Appendix I) from the sMRI dataset (44 features are selected in this work)
2) Class values are assigned as nominal/binary (0, 1) values; 0 represents healthy subjects and 1 stands for depressed subjects.
3) All the features are ranked using four FS methods: one rule (OneR), support vector machine (SVM), information gain (IG), and ReliefF with Ranker search method.
4) The feature rankings are tabulated from highest to lowest for the four methods.
5) New datasets are created from each feature ranking result; Top 1 – Top 10, Top 15, Top 20, Top 25, Top 30, Top 35, Top 40, and Top 43.
6) The new datasets are named according to format; Top <Ranking No.>_<Feature Evaluator Name>. Each evaluator has 17 sets, thus, there are 68 new dataset formed from this combination.
7) Ten classifiers are selected for the classification: Naïve Bayes, SVM Radial Basis Function (SVM RBF), SVM Sigmoid, J48, Random Forest, Random Tree, Voting Feature Intervals (VFI), LogitBoost, Simple KMeans Classification Via Clustering (KMeans), and Classification Via Clustering Expectation Minimization (EM).
8) The results are displayed in ranked order (highest first) using the accuracy (ACC) percentage. ACC is the probability that a diagnostic test is correctly performed, or the number of samples correctly classified. The ACC is calculated by the formula:

$$ACC = (TP + TN)/(TP + TN + FP + FN) \quad (6)$$

Where, True Positives (*TP*) are correctly classified positive cases, True Negatives (*TN*) are correctly classified negative cases, False Positives (*FP*) are incorrectly classified negative cases, False Negatives (*FN*) are incorrectly classified positive cases.

9) Calculations are done for the total frequency (f) of each of the features contributed towards ACC of ≥ 70%, ≥ 75%, ≥ 80% and ≥85%.
10) Based on the frequency data, calculation of the proposed DoC is performed and the associated results are stored.

11) New subset and classification process are formed using the achieved results (repeat step 5-8). Final results obtained.

IV. Experimental Results

A. Classification Performances of Existing FS Algorithms

Table I shows the ACC, F-measure, and area under the curve (AUC). The results displayed are only for the combination that achieved accuracy greater than or equal to 80%. The highest accuracy achieved was 85.29% using the SVM-EM algorithm and IG-Random Tree algorithm.

B. Degree of Contribution (DoC)

From the results obtained as partly shown in Table I, we computed the frequencies of each of the features contributed to the accuracy of ≥ 70%, ≥ 75%, ≥ 80% and ≥85%. Then, the corresponding DoC value is calculated. The DoC is converting the frequency into a 360° representation. The DoC for each feature at defined threshold setting is shown in Table II. From Table II, the Top 3 features contributed to ACC≥70-85 are the same while the top 4 features contributed to ACC≥70-80 are the same. When the ACC limit was set to 70, the DoC value was gradually reduced at one degree different between rankings. The top 1 (ltotgm) in the ranking doubled the frequency for features on ranked number 13 and 14. For ACC≥75, it doubled features on ranked 11 (rhippoc) and 12 (rtotgm). When the ACC limit was set to 75, the features are the same with (ACC≥70) for the first 19 but the ranking and DoC values are dissimilar.

Specifically, when the ACC limit was set to 80, the Top 1 and 2 has significantly higher DoC compared to the rest. The DoC drop significantly from Top 2 to Top 3 features. Then, the DoC is either maintained or reduces 3° between rankings. Interestingly, when the ACC limit set to a higher value (85%), we could perceive that only 18 features contributing and the DoC for the Top 4 features is actually doubled the remaining.

C. Performances Comparison between DOC based FS with Existing FS Algorithms

We run a preliminary classification experiment in order to evaluate the effectiveness of the proposed DoC. We created twelve subsets for each ACC limit consisting of Top 1-10, Top 15 and Top 20. The best accuracy result is 88.23% that was obtained by the DoC (ACC≥85) and DoC (ACC≥80), classified using the Random Forest classifier. It is 3% better than the existing algorithms. The DoC (ACC≥75) and DoC (ACC≥70) approach gave comparable results with the existing algorithms, scored the accuracy of 85.29%. The F-measure is reasonably high for the accuracy results above 85% with score at average of 0.9.

V. Discussions

To our knowledge, this is the first study that evaluates the volumetric features of depression patients for the purpose of depression detection of an individual. We have several combination between the FS-classifier algorithms that have given good accuracy results above 80% in our preliminary trials.

The proposed DoC calculation is to ease the process of determining the exact DoC for each of the features. Also, the proposed FS based on DoC value has shown the potential to assist FS using the DoC ranking. In DoC algorithm, the final feature ranking is produced after the multi-rule evaluation done using various evaluators-classifiers. The main advantage of this algorithm is that it considers various possible combinations before a final ranking can be computed thus it is more accurate.

TABLE I. Average accuracy (ACC), number of features (N), F-Measure, Area under the Curve (AUC)

Evaluator	Classifier	N	Accuracy	F_measure	AUC
SVM	EM	7	85.2941	0.9123	0.6875
IG	RandomTree	15	85.2941	0.9123	0.6875
ReliefF	J48	30	82.3529	0.8966	0.4856
IG	J48	35	82.3529	0.8966	0.4856
SVM	Kmeans	1	82.3529	0.8929	0.6683
SVM	Kmeans	7	82.3529	0.8929	0.6683
All	NaiveBayes	44	82.3529	0.8966	0.5962
SVM	RandomForest	8	82.3529	0.8966	0.7163
IG	RandomForest	6	82.3529	0.8966	0.7188
IG	RandomForest	15	82.3529	0.8929	0.6875
ReliefF	RandomTree	3	82.3529	0.8966	0.6250
ReliefF	RandomTree	5	82.3529	0.8966	0.6250

TABLE II. Top 20 features ranked by DoC of features contributed to accuracy (≥70%, ≥75%, ≥80% and ≥85%).

	ACC≥70		ACC≥75		ACC≥80		ACC≥85	
No	Features	DoC	Features	DoC	Features	DoC	Features	DoC
1	ltotgm	18.31	ltotgm	20.58	ltotgm	27.27	ltotgm	32.73
2	lhemis	17.41	lhemis	19.57	lhemis	24.55	lhemis	32.73
3	lnonlgm	16.51	lnonlgm	18.36	lnonlgm	19.09	ltotcsf	32.73
4	ltotcsf	13.60	ltotcsf	14.63	ltotcsf	19.09	nvcsf	32.73
5	cerebrm	13.37	wholebr	14.53	nvcsf	19.09	lnonlgm	16.36
6	wholebr	13.30	cerebrm	13.21	wholebr	16.36	wholebr	16.36
7	tothippoc	13.30	tothippoc	12.91	lnvcsf	13.64	lnvcsf	16.36
8	lnvcsf	12.48	lnvcsf	12.81	lvent	13.64	lvent	16.36
9	lvent	11.43	nvcsf	11.70	rhippoc	13.64	rhippoc	16.36
10	nvcsf	10.91	lvent	11.40	ltotwm	13.64	ltotwm	16.36
11	rhippoc	10.54	rhippoc	10.99	lgmles	10.91	lgmles	16.36
12	rtotgm	9.27	rtotgm	9.68	totgm	10.91	totgm	16.36
13	ltotwm	8.97	ltotwm	9.18	nonlgm	10.91	nonlgm	16.36
14	rgmltc	8.97	lgmles	9.18	lnonlwm	10.91	lnonlwm	16.36
15	lgmles	8.74	totgm	8.47	totvent	10.91	totvent	16.36
16	totcsf	8.52	totcsf	8.27	cerebrm	8.18	ltotles	16.36
17	totgm	8.29	nonlgm	8.07	tothippoc	8.18	rgmles	16.36
18	nonlgm	8.00	rgmltc	7.87	ltotles	8.18	lwmles	16.36
19	rnonlgm	7.77	rnonlgm	7.67	rgmles	8.18	cerebrm	0.00
20	rnonlwm	7.47	ltotles	7.57	lwmles	8.18	tothippoc	0.00

The preliminary experimental results with DoC as FS showed that better results are obtained for higher value of accuracy threshold. Specifically, when DoC (ACC≥85%) and DoC (ACC≥80%), the highest accuracy 88.23% in the classification is obtained, 3% better than the result obtained by SVM FS algorithms. Thus, future work should investigate the optimal threshold ACC value. This experimental finding suggests that the FS by DoC approach has potential to enhance the existing feature selection procedures to improve the detection accuracy.

This study also found that the left-brain dominated the feature location followed by a combination of both sides of brain. When the ACC threshold was set to ≥85%, left-brain dominated with total of 229 DoC. The best 4 features with the same DoC of 32.73 are ltotgm, lhemis, ltotcsf and nvcsf. Reported works in depression at group-level statistical analysis supports some of these features findings [5].

VI. Conclusion

In this paper, we have presented an algorithm for DoC calculation. The results in this study suggest that the proposed DoC framework enables a potentially good classification results thus could assist for a more accurate feature selection process. From the preliminary experiments, it can be seen that FS by DoC performed better than the existing feature evaluator algorithms. From DoC analysis, the DoC of each volumetric feature for the depression detection was determined with volumetric features from the left-brain dominated the contribution to depression detection. Future works to enhance the implementation of this algorithm include an investigation of the optimal threshold/limit for the ACC. We also plan to explore the FS based on the value of average merit and value of DoC rather than only the feature ranking.

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Appendix

APPENDIX I. VOLUMETRIC FEATURES

No	Attributes	Description
1	nonlgm	Non-lesion gray matter (GM) volume in whole brain
2	gmles	Subcortical gray matter lesion (GML) volume in cerebrum
3	totgm	Total GM volume
4	nvcsf	Non-ventricular CSF volume in the whole brain
5	totvent	Total Lateral ventricle volume
6	totcsf	Total CSF volume
7	nonlwm	Non-lesion white matter (WM) volume in whole brain
8	wmles	WM lesion volume in the cerebrum
9	totwm	total WM volume
10	totles	total lesion volume
11	wholebr	whole brain volume
12	lnonlgm	Non-lesion GM volume in left cerebral hemisphere
13	lgmles	Subcortical GML volume in the left cerebral hemisphere
14	ltotgm	left hemisphere total GM volume
15	lnvcsf	Non-ventricular CSF volume in left cerebral hemisphere
16	lvent	Lateral ventricle volume in left cerebral hemisphere
17	ltotcsf	left hemisphere total CSF volume
18	lnonlwm	Non-lesion WM volume in left cerebral hemisphere
19	lwmles	WML volume in the left cerebral hemisphere
20	ltotwm	left hemisphere total WM volume
21	ltotles	left hemisphere total lesion volume
22	lhemis	left hemisphere volume
23	rnonlgm	Non-lesion GM volume in right cerebral hemisphere
24	rgmles	Subcortical GML volume in the right cerebral hemisphere
25	rtotgm	right hemisphere total GM volume
26	rnvcsf	Non-ventricular CSF volume in the right cerebral hemisphere
27	rvent	Lateral ventricle volume in the right cerebral hemisphere
28	rtotcsf	right hemisphere total CSF volume
29	rnonlwm	Non-lesion WM volume in right cerebral hemisphere
30	rwmles	WML volume in the right cerebral hemisphere
31	rtotwm	right hemisphere total WM volume
32	rtotles	right hemisphere total lesion volume
33	rhemis	right hemisphere volume
34	cerebrm	cerebral volume
35	lgmtc	Left caudate GM volume
36	lgmltc	Left caudate lesion volume
37	rgmtc	Right caudate GM volume
38	rgmltc	Right caudate lesion volume
39	lputamn	Left putamen volume
40	rputamn	Right putamen volume
41	lhippoc	Left hippocampus volume
42	rhippoc	Right hippocampus volume
43	totputamn	total putamen volume
44	tothippoc	total hippocampus volume