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ADAPTATIVE ALGORITHMS FOR AUTOMATIC DETECTION OF WHITE MATTER HYPERINTENSITIES IN VASCULAR AND NEUROLOGICAL DISEASE: A SYSTEMATIC REVIEW

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ABSTRACT
This review article covered 20 years of published papers on the detection of lesions of vascular and neurological origin on Magnetic Resonance Imaging (MRI). The article provided concrete suggestions about pulse sequences and algorithms for the jointly detection of lesions in the white matter. The algorithm with the best adaptive features was Histogram. The results suggested to perform comprehensive studies that evaluate segmentation algorithms on different types of lesions.

KEYWORDS: neuroimages, algorithm, segmentation, vascular and neurological diseases.
MSC: AMS subject classifications

RESUMEN
Este artículo de revisión abarca 20 años de trabajos publicados sobre la detección de lesiones de origen vascular y neurológico en Imágenes de Resonancia Magnética (IRM). El artículo proporciona sugerencias concretas sobre secuencias de pulso y algoritmos para la detección conjunta de lesiones en la materia blanca. El algoritmo con las mejores características de adaptabilidad fue Histograma. Los resultados sugierieron realizar estudios integrales que evaluen algoritmos de segmentación en diferentes tipos de lesiones.

PALABRAS CLAVE: neuroimágenes, algoritmo, segmentación, enfermedades vasculares y neurológicas.

1. INTRODUCTION

In neuroimage, lesion segmentation includes designed algorithms to identify, delimiter and characterize regions with some damages. These algorithms are oriented by heuristics (patterns and *a priori* information) and anomalies that highlight on specific features (color, position and brightness). For the detection of vascular and neurological lesions, the white matter hyperintensities are used as a selection criteria due to the high contrasts between healthy and affected regions. In Magnetic Resonance Imaging (MRI), high contrasts are signal of damage in the integrity of the white matter and high fluidity too [13].

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A segmented region is the result of identifying all pixels or voxels that composes and limits it. Although, the procedure is mainly based on the intensity of the pixels; attributes such as texture can be considered. In general, the segmentation process uses pattern recognition algorithm for processing medical images with high variability [6]. Segmentation algorithms are grouped into two learning categories: supervised and unsupervised. Yet, they can be automatic or semi-automatic if, at some point in the processing, the human intervention is required or not [7].

The segmentation of White Matter Lesions (WML) is performed on weighted images T1, T2, FLAIR, PD, T2* and multimodal sequences (T1,T2; T2,FLAIR; T1,FLAIR and others). In the process, some sequences provide more information than others, with different characteristics. For example, FLAIR provides better information than T2 for delimiting damaged regions in lesions with vascular origin[18]. However, FLAIR could overestimate lesions in the posterior fossa region in which T2 provides better sensitivity. The combination of both sequences complement the results and reduce false positives. White matter lesions may variate their shape like: periventricular caps, rims or halos[28]. In neurophysiology, two fundamental types are recognized: periventricular (PVWML) and deep (DWML). A lesion is called PVWML, if it is located less than 1cm from the ventricles. For example: a PVWML is considered DWML when either its shape is irregular or its extension is prolonged. Dadar and colleagues [9] demonstrated the ease of segmenting PVWML lesions with the T1. The evidences prove the complexity of the segmentation process and the details to be consider.

White Matter Hyperintensities (WMHs) has high correlation with many clinical disorders including cerebrovascular and neurological disorders. In general, cerebrovascular origins are common in Alzheimer's disease (AD) and vascular dementia [5, 34]. AD co-occurs with cerebral small vessel disease (SVD) and hypertension [9]. WMHs resulting from SVD has been associated with vascular risk factors like hypertension [2]. In patients with SVD, the risk of dementia and Parkinson's disease increases, also associated with cognitive, motor, and mood disturbances [17]. Mild cognitive impairment (MCI) has been associated with Parkinson's disease, cerebrovascular accident and other disorders.

This work studies the automated methods proposed for the segmentation of hyperintensities in white matter (WMH), according to the nature of the lesions in MRI. The comparative analysis considers the characterization schemes and selected sequence. The analysis might conduct upcoming researches in the creation of hybrid algorithms and consequently the correct detection and segmentation of White Matter (WM) lesions of vascular and neurological origin.

2. MATERIALS AND METHODS

SEARCH STRATEGY AND SELECTION CRITERIA

The review was conducted according the guidelines of systematic reviews and meta-analysis (PRISMA)[36]. The selected articles were published from January 2000 to March 2022 in PubMed, IEEEXplore, and ScienceGov databases. The keywords used were segmentation, automatic detection, algorithms and white matter. The queries were a combination of keywords and the selection was limited to studies published

in English. In addition, reference lists were used to improve the search and identify other studies about the same subject. Autors used JabRef to identify relevant papers and eliminate duplicates. Conference abstracts, letters to the editor, case reports, guidelines and protocols were excluded. Also, systematic reviews and meta-analysis were discarded. The withdrawal strategy allowed to reduce the selection biases, ensuring homogeneity in the content of selected publication.

A first approach considered the presence of selected words in the title, the abstract and the keywords. This strategy removed papers with relevant terms in the corpus of the manuscript. All published studies using automatic or semi-automatic algorithms for the segmentation of the hyperintensities of neurological or vascular origin were included. Yet, studies on Magnetic Resonance Imaging (MRI) in adult humans were considered.

DATA EXTRACTION

The metadata of the articles was gathered by 2 reviewers and a third one verified the data. The data collected included name of the algorithm, sample, sample size, sequences and quality control. The algorithms were evaluated with the measures established in the next subsection. Validation measure of each algorithm was recovered from the original paper. Although a subset of the metrics are referenced, only those in common are used to compare the algorithms.

This review was oriented to the identification and analysis of segmentation algorithms which results have been promising in different types of degenerative diseases. These techniques are considered adaptative due to their ability to segment injuries of different nature.

METRICS TO EVALUATE EFFICIENCY OF ALGORITHMS

Three equivalent metrics were selected to evaluate the accuracy and consistency of algorithms[37, 65]: Dice Similarity Coefficient (DSC), F_1 score and Similarity Index (SI). The DSC values, F_1 and SI takes values into the range $[0, 1]$ where low coefficients indicate no spatial overlap and those close to 1 mean absolute overlap [21, 4]. According to literature, these three overlap metrics a 0.7 score or higher indicates good segmentation. In the analysis, the term overlap metric (OM) represented DICE, F_1 and SI measures to avoid ambiguity.

3. RESULTS

The search returned 134 unique citations (Figure 1), of which 71 were excluded at the title and abstract lecture. Furthermore, 25 articles were excluded after full-text review. Finally, 43 studies were selected for evaluation in this review; 31 focused on diseases of neurological origin and 12 on diseases of vascular origin.

Table 1 shows the performance of sequences in a particular disease. The quality coefficients were the means of OM evaluations between methods grouped by disease and sequence. The coefficients were bounded between 0 and 1 while their color interpretation varied between light and dark blue. Table 2 summarized the result of proposed methods with at least two tested applications. In this table, highlighted patterns

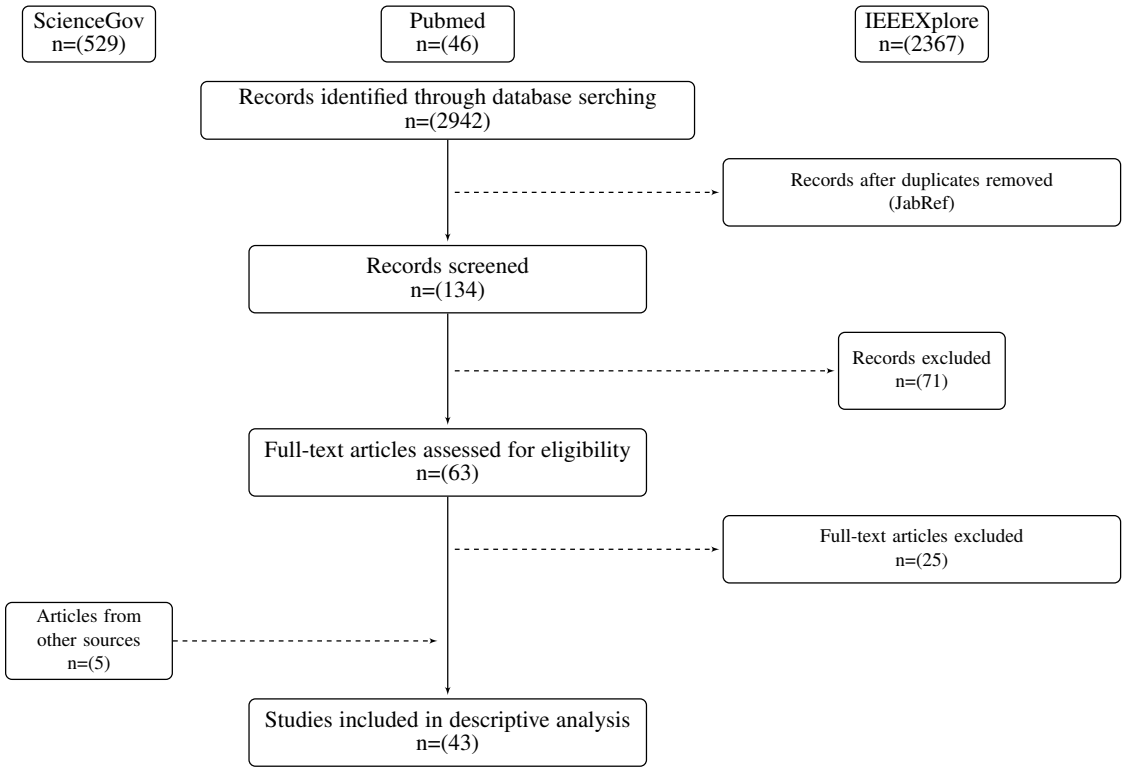

Figure 1: **Design of the study.** Flow of studies identified in literature search for systematic review on segmentation of white matter lesions.

evidence adaptive characteristics in methods on different types of lesion. These algorithms have been developed based on MRI modalities: T1, T2 and Fluid Attenuated Inversion Recovery (FLAIR) and multiple combinations. Literature cited FLAIR as the sequence with the highest accuracy among the MRI modalities for identifying the White Matter Lesion (WML). Single-modal methods are useful to segment the brain into base regions such as white matter (WM), Grey Matter (GM), and Cerebrospinal Fluid. In contrast, multimodal methods have been preferred for more robust lesion detection, despite the high cost of acquiring multimodal MRI data.

3.1. NEUROLOGICAL DISEASE

Magnetic Resonance Imaging (MRI) data of older subjects exhibit features of abnormal brain white matter such as tissue loss with ventricular enlargement and WML. This pattern is not usual on scans of younger adults [61]. MRI scans performed in clinical inquiries showed an increase of WMLs in the healthy elderly.

A lesion in Multiple Scleriosis (MS) is an area of focal hyperintensity on a T2, T2,FLAIR or a proton density (PD), weighted sequence. MS lesions vary from round to oval shape and involve regions from a few millimeters to two centimeters in diameter. They can appear in both hemispheres, but their distri-

Table 1: Heat map created by OM coefficients as a quality measure of each sequence on a disease. The values are the means quality (OM) obtained from algorithms group by sequence and disease.

Sequences \ Disease	MS	AD	MCI	PD	DLB	VD	BI	H	IS	CDL	References
PD	0.95										[49]
DWI									0.85		[60]
FLAIR	0.63	0.64						0.83			[9, 29, 59]
T1,T2	0.46								0.70		[52]
T1,FLAIR	0.53	0.84	0.70	0.94	0.94		0.63	0.77	0.57	0.76	[3, 20, 39, 46, 50, 51, 62]
T2,FLAIR	0.68								0.76		[8, 64]
DWI,FLAIR									0.76		[32]
T1,T2,FLAIR	0.55	0.71	0.75			0.78					[3, 11, 12, 24, 33, 41, 48, 57, 58]
T1,T2*,FLAIR									0.89		[42]
T1,DWI,FLAIR							0.83		0.80		[53]
PD,T1,T2,FLAIR	0.57										[45, 55, 56]
T1,T2,ADC,FLAIR										0.60	[35]

MS: Multiple Scleriosis, AD: Alzheimer's disease, MCI: Mild Cognitive Impairment, PD: Parkinson's disease, DLB: Lewy body dementia
VD: Vascular Dementia, BI: Brain Infart, H: Hypertension ,IS: Ischemic Stroke
CDL: Cerebral Autosomal Dominant Arteriopathy with Subcortical Infarcts and Leucoencephalopathy (CADASIL)

bution is often mildly asymmetric in the early stages. These lesions affect not only the periventricular and juxtacortical white matter but also the corpus callosum [16].

In MS lesion detection, automated and semiautomated approaches have been proposed in literature. LaRosa and colleagues [30] proposed a fully convolutional deep learning approach based on U-Net using T1 and FLAIR sequences. In addition, U-Net was used by Aslani and colleagues [3] with T1, T2 and FLAIR sequences. Sudre and colleagues [52] proposed an adaptive framework for data modelling in the presence of multiple outliers, named BaMoS (Bayesian Model Selection).

Alzheimer's is the most common form of dementia that currently affects 44 million people worldwide and is increasing in prevalence. White matter hyperintensities (WMHs) are highly prevalent in AD patients as well as the elderly population. Larger WMH volumes have been associated with AD and cognitive decline [54]. The lesions emerged close to the cerebral ventricles [9].
Recently, BaMoS models were applied by Fiford and colleagues [15] for WMH segmentation in Alzheimer's. They proposed the same pulse sequences in [57] with rigidly coregistered in T1 space. In [24], Ithapu proposed Support Vector Machine (SVM) methods base on texture and intensity-variation features. Subcortical vascular dementia is a neurodegenerative disorder that leads to a progressive decline in memory and cognitive function. It is considered a common cause of dementia. Although, It is caused by various types of cerebrovascular diseases (ischemia or hemorrhage). In the segmentation of WMH regions in subcortical vascular dementia, Kawata and colleagues [27] proposed two segmentation methods. Region-growing and a level-set method were combined to propose an hybrid solution that use an automatic and adaptive strategy to select the best methodology for each WMH region based on its image features.

Table 2: Methods of studies with application on lesions with vascular and neurological origin.

Algorithm	Ref	Sample	n[b]	Sequences	Metric
BaMoS	[52]	Multiple Scleriosis	20	T1,T2	0.46
	[15]	Alzheimer's disease	60	T1, FLAIR	0.74
LST	[3]	Multiple Scleriosis	51	T1, FLAIR	0.30
	[24]	Alzheimer's disease	251	T1, T2, FLAIR	0.41
U-Net	[30]	Multiple Scleriosis	90	T1, FLAIR	0.62
	[60]	Ischemic Stroke	429	DWI	0.85
	[3]	Multiple Scleriosis	51	T1, T2, FLAIR	0.63
MRF	[26]	Multiple Scleriosis	25	T1, T2, FLAIR	0.69
	[44]	Hypertension	24	T1, FLAIR	0.70 [a]
SVM	[24]	Alzheimer's disease	251	T1, T2, FLAIR	0.54
	[27]	Vascular dementia	10	T1, T2, FLAIR	0.78
C-SVM	[10]	Alzheimer's disease,Lewy body dementia,Parkinson's disease	102	T1, FLAIR	0.94
BIANCA	[19]	Alzheimer's disease, MCI	85	T1, T2, FLAIR	0.75
		Ischemic Stroke	474	T2, FLAIR	0.76
	[31]	CADASIL	66	T1, FLAIR	0.80
Histogram	[53]	Ischemic Stroke	30	T1,DWI,FLAIR	0.83
	[23]	MCI	30	T1, FLAIR	0.78
AMOS-2D	[43]	Brain Infarct , MCI	28	T1, FLAIR	0.63

[a] Exact values were not available, reported values are calculated from TP, TN, FP and FN.
[b] Sample size.

Damangir and colleagues [10] proposed a cascade of reduced Support Vector Machine (C-SVM) method with active learning for WMHs segmentation in cases with Alzheimer's disease, Lewy body dementia and Parkinson's disease. Dementia with Lewy bodies (DLB) is a common variant of cognitive impairment with Parkinson's dementia that include a spectrum of neurodegenerative dementias. Thus, the term Lewy Body Disease is currently used to describe neurodegenerative conditions with similar clinical phenotype (dementia combined with parkinsonism) and lower levels of $\alpha-$synuclein [63]. WMHs can be visualized as focal punctate areas of high intensity signal on T2 images. They have been reported to be similar in DLB and AD [22]. Parkinson's disease is a neurodegenerative disorder characterized by a range of motor, non-motor features and neurobehavioral dysfunction [14]. Their lesions appear as hyperintense periventricular signal on FLAIR sequences from MRI.

3.2. CEREBROVASCULAR DISEASE

Focal White Matter Hyperintensities has been associated with various disorders related to Cerebrovascular Disease [50]. Vascular dementia is the manifestation of a cerebrovascular disease and the second most frequent type of dementia following Alzheimer's disease. Griffanti and colleages [19] develop BIANCA (Brain Intensity AbNormality Classification Algorithm), a supervised method for WMH detection based on the k-Nearest Neighbor (kNN) algorithm. They proposed this method for patient population whith neurodegenerative and vascular disease.

Roy and colleagues[44] used a Random Forest (RF) classifier to generate lesion probability score for each pixel in the brain region. Such scores were integrated into a Markov Random Field (MRF) cost function to obtain the final segmentation by removing false positives. This method processes multispectral information from T1 and FLAIR intensities for hypertension lesion segmentation. White matter hyperintensities (WMHs) are common in patients with acute cerebral infarction and its presence increases the risk of Stroke, Cognitive Impairment and death [53]. Stroke lesion appears as hyperintense signal in T2 from Magnetic Resonance Imaging (MRI) [40]. There are few segmentation algorithms that just use T1 weight image for Stroke lesions. Even thought, multimodal MRI sequences including Diffusion Weighted Imaging (DWI), T2,FLAIR, and Perfusion Weighted Imaging are used to detect the presence of Stroke lesions in the first few hours of an incident [25]. Tsai and colleagues [53] proposed to segment WMHs by empirical threshold and atlas information. This method subtract white matter voxels affected by acute infarction in Ischemic Stroke. The procedure combined information from T1, FLAIR and DWI sequences.

The BIANCA algorithm was used by Ling and colleagues [31] to segment extensive white matter lesion caused by Cerebral Autosomal Dominant Arteriopathy with Subcortical Infarcts and Leucoencephalopathy (CADASIL). They used three strategies to select the threshold that is applied to the probabilistic output of BIANCA. They proved that BIANCA is a reliable and fast segmentation method to extract masks of WMH in patients with extensive lesions.

There are many medical disorders known to have a positive association with MCI [1]. For example, Parkinson's disease, traumatic brain injury, cerebrovascular accident, Huntington disease, and human immunodeficiency virus. Cognitive impairment or behavioral symptoms are manifested in early stages of a neurodegenerative disease. The symptoms are common in disorders such as Alzheimer's disease, Vascular dementia, Lewy body disease, Prion disease and Frontotemporal dementia [34] [47]. In general, amnestic MCI led to Alzheimer's or Vascular dementia[38]. Whereas nonamnestic MCI produces frontotemporal dementia or Lewy body disease [38]. Iorio and colleagues [23] proposed a semi-automated method based on the segmentation of intensity Histogram on FLAIR images. This algorithm was performed using FSL and SPM which are freely available software. Few algorithms are been tested in Mild Cognitive Impairment like BIANCA ([19]) and AMOS-2D ([43]).

To evaluate the quality of each algorithm in neurological and vascular disease, the Figure 2 customizes the quality in a scale of color and coefficients of OM. The possible values are bounded between 0 and

1. Their representation in the Barcolor is a gradient that varies between light and dark blue. Figure 3 represents each algorithm with its mean coefficients in Vascular and Neurological group. For this reason, the graph includes a red line $x = y$ as a position reference of balance and compromise between both group. In the graph, an algorithm with null value in an axis means the absence of results on the group associated. The 2D space was divided in 4 quadrants according to middle of both axis and their limits. In the graph, the first quadrant is found in the upper-left corner and limited by 0.5-1 in Vascular disease and 0-0.5 in Neurological disease. It includes methods with high quality (> 0.5) in the segmentation lesions due to Vascular disease but poor (< 0.5) results for cases with Neurological origin. The second one represents methods with low performance in both group with OM coefficients less than 0.5. The third group represents methods with low quality in vascular group (< 0.5) and high acquire (> 0.5) in neurological lesions. The last quadrant involves algorithms with high quality (> 0.5) in both group of lesions.

4. DISCUSSION

This article customizes the principal approaches for segmentation of white matter hyperintensities on MR images acquired from patients with neurological or vascular disease. In clinical practices, the right selection of pulse sequence is relevant to obtain high quality in the segmentation process. The Table 1 presents the quality reached with different sequences in the process to segment lesions caused by each type of disease.

In Multiple Sclerosis (MS), the sequence with the highest coefficient (0.95) was Proton Density (PD). The sequence T1,T2 was the least relevant with 0.46 as OM coefficient. In Alzheimer's disease, the diversity of sequences used is less than MS and it has the highest quality coefficient with T1,FLAIR but the lowest with FLAIR. This evidence how the combination of anatomical image T1 and FLAIR improve the segmentation results. Mild cognitive impairment is a disease with poor information on the best sequence to use. However, two combination were applied in experimental researches: T1,T2,FLAIR (0.75) and T1,FLAIR (0.7). In this case, the inclusion of T2 did not brought significant improvement to the process. It is well-know that FLAIR and T2 bring the same information but the first one with less noise [7].

In Parkinson's disease, T1,FLAIR was the only sequence used with C-SVM and reached the high score: 0.94. A similar result obtained this algorithm on Lewy body dementia. The T1,T2,FLAIR was the sequence used to segment lesions caused by Vascular dementia with 0.78. In Brain infarct, two sequences were proposed: T1,DWI,FLAIR and T1,FLAIR. The first one was the most suitable with 0.83 while the T1,FLAIR sequence reached 0.63. The studies on Hypertension evidence better results just using FLAIR without T1 sequence. The Ischemic Stroke was the second disease with more results on different sequences. Although DWI is the most suggested in clinical practices, the community have been looking for another alternatives. In this case, T1,T2*,FLAIR guaranteed high quality over the rest with 0.89 follow it by DWI (0.85). On CADASIL, the only known result was using T1,FLAIR with WHASA algorithm and its OM coefficient was 0.76.

In the Figure 2, the algorithms with more than one applications are compared by their results on different diseases. The BaMoS algorithm was testing with MR images acquired from patients with MS and Alzheimer's disease. For the first case study, it used the information obtained from T1,T2 sequence which was not the best choice for this disease (see Table 1). On Alzheimer's disease, the results were relevant with 0.74 and the sequence selected was T1,FLAIR that reached highest quality for this case in the sequence analysis. Unfortunately, the quality coefficients were less than the mean OM value for the sequences selected in both cases (Table 1).

The LST algorithm is a classic method in the lesion segmentation. For that reason, it has been considered like standard reference in comparative analysis with new approaches. In the last decade, LST algorithm results were stemmed from original articles on novel methods in MS and Alzheimer's disease. In the first one, the OM coefficient did not reached the average value for T1,FLAIR on this disease (refer to Figure 2). The same result was found in the sequence selected for cases with Alzheimer's (T1,T2,FLAIR). In addition, the worst coefficients were obtained by this algorithm.

In the period selected for this review, the applications of neural network increased in the field of image processing to resolve segmentation problems. The U-Net algorithm was proposed to identify WMH lesions on patients with Multiple Scleriosis (MS) in two articles with T1,FLAIR and T1,T2,FLAIR (see Table 2). However, the improvement between the first study to the second one was insignificant. The inclusion of T2 sequence did not bring relevant information in the segmentation process. Although the selected sequences were not the best choice for this type of lesions, the OM coefficients were better than the estimated average (Table 1). Another research was oriented to detect regions with damages caused by Ischemic Stroke from DWI images, reached satisfactory results [60].

The Markov Random Forest algorithm obtained similar coefficients on MS and Hypertension. In MS, the algorithm surpass the OM average for T1,T2,FLAIR sequence. However, the quality was lower than the expected mean on Hypertension with T1,FLAIR.

The SVM algorithm represents a group of supervised strategies and it has proved to be useful in medical applications from previous researches. The results were obtained applying the same sequence on Alzheimer's disease (AD) and Vascular dementia (VD): T1,T2,FLAIR. The quality for AD was poor than the mean estimated with this sequence and the same for VD. In [10], the authors proposed a new variant of SVM and tested with data from patients with Lewy body dementia, Alzheimer's and Parkinson's disease. In general, C-SVM maintained the same high quality using T1,FLAIR sequence with 0.94. It was the algorithm with highest performance among the methods selected by multiple applications (Figure 2).

BIANCA is a supervised algorithm based on kNN optimized to detect lesion on patients with neurodegenerative and vascular disease. It was included in FSL toolbox and support different MRI protocols. The results with T1, T2, FLAIR were similar to the mean for Alzheimer's and Mild Cognitive Impairment with 0.75. In addition, the quality for Ischemic Stroke did not change too much with 0.76 using

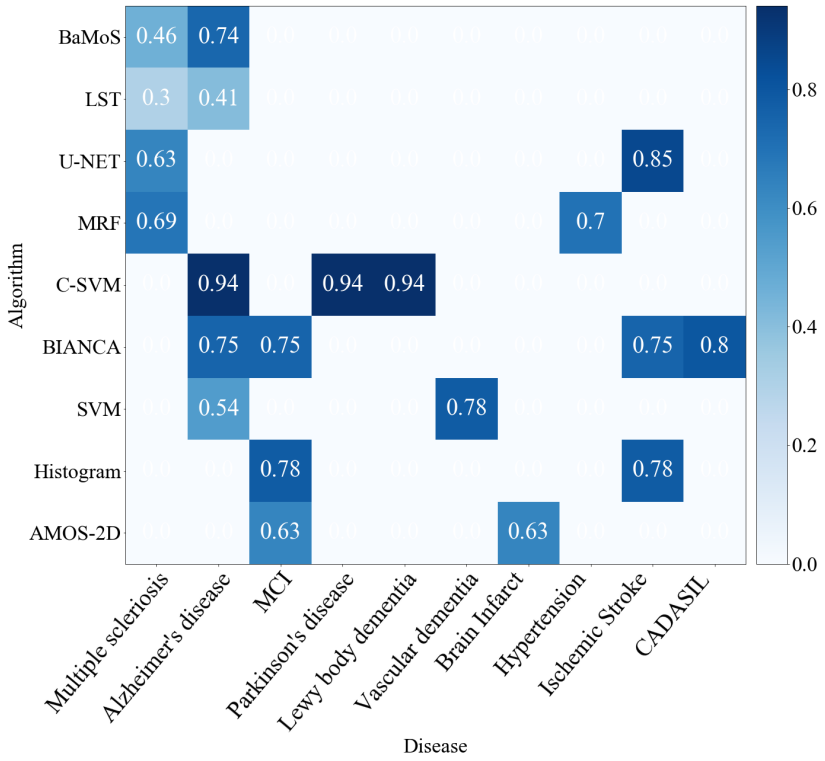

Figure 2: Heat map based on the OM coefficient of the algorithms used in each type of disease.

T2,FLAIR. However, their results in CADASIL were above the mean OM coefficient with the T1,FLAIR sequence. This algorithm is an adaptive approach for both disease groups. Histogram is another promising algorithms for lesion segmentation of vascular and neurological disease. For Ischemic Stroke, this algorithm increment the mean of OM values with the sequence T1, DWI, FLAIR summarizes on Table 2. Also, it obtained good performance on Mild Cognitive Impairment using the sequences T1,FLAIR. However, the algorithm AMOS-2D with the same sequence obtained low quality (refer to Table 1) on Brain Infarct and Mild Cognitive Impairment with an OM coefficient below to the average.

In the Figure 3, the selected algorithms are represented in a 2D space defined by their quality on Vascular and Neurological disease. Almost all of them are located in the four quadrant except: LST, BaMoS and C-SVM. These three algorithms have just relevant results in neurological disease and the best one was C-SVM with 0.94. In the four quadrant, the algorithms farthest from the red line are SVM and U-Net. Both with more quality in vascular than neurological disease. The algorithms closest to the red line are AMOS-2D, MRF, BIANCA and Histogram which evidence adaptative quality for both type of disease. Among them, Histogram obtained highest results follow by BIANCA. In addition, AMOS-2D shows a better compromise in the lesions segmentation between vascular and neurological diseases. However, it was the lowest performing algorithm in this quadrant below 0.7. Another potential candidate is C-SVM because had better results than Histogram on neurological lesions. Its performance on lesions of vascular

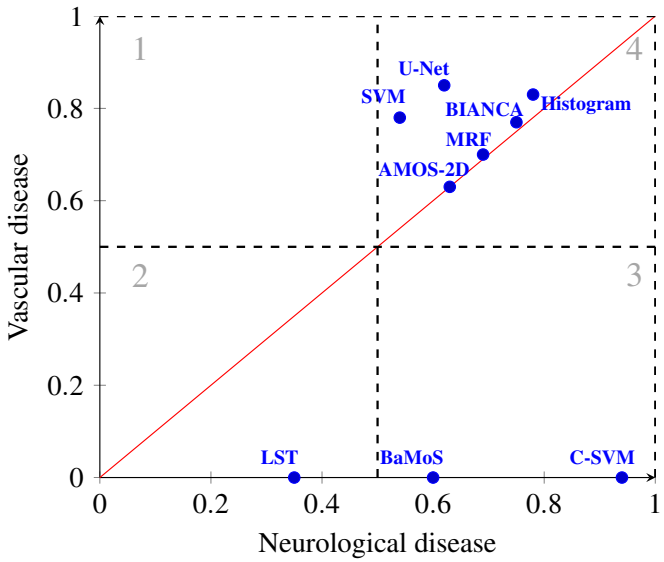

Figure 3: Algorithm with its mean coefficients in Vascular and Neurological group.

origin lacks evidence, but its methodology is similar to SVM that reached relevant results for this type of lesions. The U-Net algorithm reached the most relevant results on lesions with origin in vascular disease.

5. CONCLUSION

The sequence T1,FLAIR was the best choice in the lesion segmentation for both vascular and neurological disease. Their most relevant results were on Alzheimer's, Parkinson's, Lewy body dementia and CADASIL. This sequence, in combination with $T2^*$, proved to be a great candidate as alternative to DWI sequence for Ischemic Stroke. The sequence T1,T2,FLAIR was another derivation from T1,FLAIR with high performance on lesions of Ischemic Stroke and MCI. A suggestion for future work is a more deep evaluation for PD sequence in the segmentation process due to their results on MS.

In the comparative analysis, Histogram conserved high and stable OM coefficients in the segmentation of lesions from vascular and neurological disease. This algorithm with a simple methodology has proved to be useful for the clinical practices when the information about the type of lesion is poor. Although, BIANCA was not an algorithm with a relevant quality, it was designed to detect White Matter Hyperintensities without take account their origin. The algorithm C-SVM reached highlight results on neurological lesions. However, the revision process did not find any evidences of applications on lesions of vascular origin. This approach is a promising technique and should be test it their performance on lesions of vascular origin in future works.

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