Prostate Segmentation in Magnetic Resonance Images using Artificial Neural Networks- A Systematic Literature Review

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I. Introduction

This document presents the supplementary materials of the Systematic Literature Review (SLR) for Prostate Segmentation in Magnetic Resonance Images using Artificial Neural Networks.

Appendix I
Inclusion and exclusion criteria

The inclusion and exclusion criteria helped to determine if a study contributed to answering the RQs. The inclusion criteria helped to capture studies of interest that were focused in prostate segmentation in MRIs using ANNs. Whereas the exclusion criteria removed irrelevant studies. These criteria were shown in Table I.

TABLE I
Inclusion and exclusion criteria used in this SLR

Inclusion criteria	Exclusion criteria
Prostate segmentation studies using artificial, feedforward or convolutional Neural Networks are included. Also, mix of artificial, feedforward or convolutional Neural Networks with other segmentation techniques are included.	Duplicate reports of the same study (when several reports of a study exist in different journals the most complete version of the study was included in the review).
Prostate segmentation studies based on MRIs are included.	All studies that do not contain MRIs.
Documents written in english are included because of the scientific relevance of this language.	All studies that do not segment the prostate.
Papers of journals or conferences published between January 1st, 2014 and December 31th, 2020.	Studies without results.

Appendix II
Quality assessment implementation

The quality assessment instrument was applied to the 66 primary studies (see Table II). As a result, one study was rejected. Therefore, 65 primary studies were obtained to extract information in the next stage.

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Appendix III
Summary of the relevant information in the primary studies analyzed for this SLR

This section presents a summary of the relevant information from the 65 studies analyzed for this SLR. The information presented was: study; year of publication; area and type of segmentation; parameter, sequence plane, and acquisition of the MRIs; availability of dataset and public dataset (see Table III).

Appendix IV
Data augmentation technique

Data augmentation techniques fell into three categories:

- *Spatial transformations:* (1) flipped, (2) rotated, (3) shifted or translations, (4) zoom or scale transformation, (5) cropping, (6) isotropic expansions, (7) non-linear or elastic transformations, and (8) affine or shearing transformations.
- *Alterations in image appearance:* (9) histogram mapping, (10) intensity scaling, (11) random gamma correction, (12) adjustment of brightness, contrast or saturation, and (13) image enhancement.
- *Alterations in image quality:* (14) channel shifting, (15) adding noise, and (16) blurring.

Figure 1 presented the data augmentation techniques, which used in 44 studies reviewed in this SLR. The remaining 21 studies did not specified any technique of data augmentation used. Also, the augmentation techniques most widely used are flipping and random rotation, which were implemented in with 32 studies and 29 studies, respectively.

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TABLE II
QUALITY ASSESSMENT IMPLEMENTATION

Study	Questions				Score
	1	2	3	4	
P1 [1]	P	P	Y	Y	3
P2 [2]	P	P	P	Y	2.5
P3 [3]	P	P	Y	Y	3
P4 [4]	P	Y	P	Y	3
P5 [5]	Y	Y	Y	Y	4
P6 [6]	Y	Y	Y	Y	4
P7 [7]	P	P	P	Y	2.5
P8 [8]	Y	P	Y	Y	3.5
P9 [9]	P	P	Y	Y	3
P10 [10]	Y	Y	Y	Y	4
P11 [11]	P	P	Y	Y	3
P12 [12]	Y	Y	Y	Y	4
P13 [13]	Y	P	Y	Y	3.5
P14 [14]	Y	Y	Y	Y	4
P15 [15]	P	P	Y	Y	3
P16 [16]	Y	P	Y	Y	3.5
P17 [17]	Y	P	Y	Y	3.5
P18 [18]	Y	P	P	Y	3
P19 [19]	Y	P	Y	Y	3.5
P20 [20]	Y	P	Y	Y	3.5
P21 [21]	P	Y	Y	Y	3.5
P22 [22]	Y	P	Y	Y	3.5
P23 [23]	Y	P	Y	Y	3.5
P24 [24]	P	P	P	Y	2.5
P25 [25]	Y	Y	Y	Y	4
P26 [26]	Y	Y	P	P	3
P27 [27]	Y	P	Y	P	3
P28 [28]	Y	Y	Y	P	3.5
P29 [29]	Y	Y	Y	Y	4
P30 [30]	P	P	Y	Y	3
P31 [31]	Y	Y	Y	Y	4
P32 [32]	P	Y	Y	Y	3.5
P33 [33]	Y	P	P	P	2.5
P34 [34]	Y	P	Y	Y	3.5
P35 [35]	Y	P	Y	Y	3.5
P36 [36]	Y	P	Y	Y	3.5
P37 [37]	Y	Y	Y	Y	4
P38 [38]	P	Y	Y	P	3
P39 [39]	Y	Y	Y	P	3.5
P40 [40]	P	P	Y	P	2.5
P41 [41]	Y	Y	Y	Y	4
P42 [42]	Y	P	Y	Y	3.5
P43 [43]	Y	Y	Y	Y	4
P44 [44]	Y	P	Y	Y	3.5
P45 [45]	P	Y	P	Y	3
P46 [46]	Y	P	Y	Y	3.5
P47 [47]	Y	Y	Y	Y	4
P48 [48]	Y	P	Y	Y	3.5
P49 [49]	P	Y	Y	Y	3.5
P50 [50]	P	P	Y	Y	3
P51 [51]	P	P	Y	Y	3
P52 [52]	P	P	Y	Y	3
P53 [53]	P	P	Y	Y	3
P54 [54]	Y	Y	Y	Y	4
P55 [55]	Y	P	Y	Y	3.5
P56 [56]	Y	Y	Y	P	3.5
P57 [57]	P	P	Y	Y	3
P58 [58]	Y	P	Y	Y	3.5
P59 [59]	Y	Y	Y	P	3.5
P60 [60]	P	Y	Y	Y	3.5
P61 [61]	Y	P	Y	Y	3.5
P62 [62]	P	Y	Y	Y	3.5
P63 [63]	Y	P	Y	Y	3.5
P64 [64]	Y	Y	Y	Y	4
P65 [65]	Y	Y	Y	Y	4

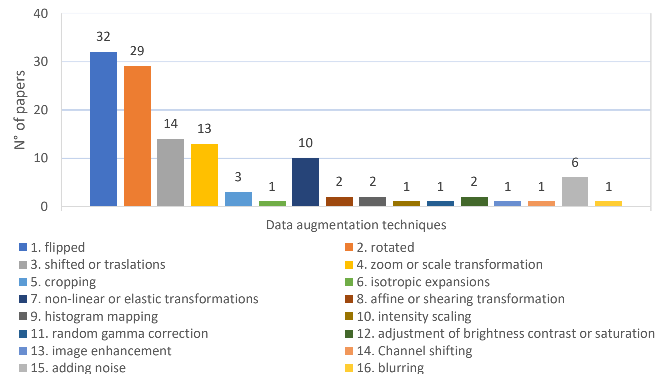

Fig. 1. Data augmentation technique used in the 44 studies reviewed in this SLR

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TABLE III
SUMMARY OF THE RELEVANT INFORMATION IN THE PRIMARY STUDIES ANALYZED FOR THIS SLR

	Year	Segmentation		MRIs				Dataset	
		Type	Areas	Parameters	Modalities	Plane	Acquisition	Type	Public
P1 [1]	2015	2D	CG,PZ	mono	T2W	axial	non-ERC	public	NCI-ISBI 2013
P2 [2]	2016	3D	WG	mono	T2W	axial	fusion	public	PROMISE12
P3 [3]	2016	3D	WG	mono	T2W	axial	fusion	public	PROMISE12
P4 [4]	2017	3D	WG	mono	T2W	axial	ERC	public	PROMISE12
P5 [5]	2017	2D	WG,CG	multi	T2W, DWI, ADC, DERIVATE	axial	undefined	private	
P6 [6]	2017	2D	WG	mono	T2W	axial	ERC	private	
P7 [7]	2017	2D	WG	mono	T2W	axial	undefined	private	
P8 [8]	2017	2D	WG	multi	T2W,CED	axial	ERC	private	
P9 [9]	2018	3D	WG	mono	T2W	axial	undefined	private	
P10 [10]	2018	3D	WG	multi	T2W, DWI	axial	ERC	private	
P11 [11]	2018	3D	WG	mono	T2W	axial	fusion	public	PROMISE12
P12 [12]	2018	3D	WG	mono	T2W	all	non-ERC	public	PROSTATEx
P13 [13]	2018	2D	WG,PZ	multi	T2W, DWI	axial	non-ERC	private	
P14 [14]	2018	3D	WG	mono	T2W	axial	ERC	private	
P15 [15]	2018	2D	WG	mono	T2W	axial	ERC	public	PROMISE12
P16 [16]	2018	3D	WG	mono	T2W	axial	ERC	public	NCI-ISBI 2013
P17 [17]	2018	3D	CG,PZ	mono	T2W	axial	undefined	private	
P18 [18]	2018	2D	WG	mono	T2W	axial	ERC	fusion	
P19 [19]	2018	3D	WG	mono	T2W	axial	ERC	public	PROMISE12
P20 [20]	2018	2D	WG	mono	T2W	axial	fusion	public	PROMISE12
P21 [21]	2018	2D	WG	mono	T2W	axial	ERC	public	PROMISE12
P22 [22]	2018	2D	WG	mono	T2W	axial	ERC	public	PROMISE12
P23 [23]	2018	2D	WG	mono	T2W	axial	ERC	public	PROMISE12
P24 [24]	2018	2D	WG	mono	T2W	axial	fusion	public	PROMISE12
P25 [25]	2019	2D	CG,PZ	mono	T2W	axial	non-ERC	private	
P26 [26]	2019	2D	WG	mono	T2W	axial	fusion	public	PROMISE12
P27 [27]	2019	2D	WG	mono	T2W	axial	fusion	public	PROMISE12
P28 [28]	2019	3D	WG	mono	T2W	axial	fusion	public	PROMISE12
P29 [29]	2019	2D	WG	mono	T2W	axial	fusion	public	PROMISE12
P30 [30]	2019	3D	WG	mono	T2W	axial	non-ERC	public	PROMISE12
P31 [31]	2019	2D	WG,TZ	mono	DWI	axial	ERC	private	
P32 [32]	2019	2D	WG	mono	T2W	axial	ERC	public	PROMISE12
P33 [33]	2019	3D	WG	mono	T2W	axial	fusion	public	PROMISE12, QIN-PROSTATE
P34 [34]	2019	3D	WG	mono	T2W	axial	ERC	public	PROMISE12
P35 [35]	2019	2D	WG	mono	T2W	axial	ERC	private	
P36 [36]	2019	3D	WG	mono	T2W	axial	fusion	public	PROMISE12, Prostate MR Image
P37 [37]	2019	2D	CG,PZ	mono	T2W	axial	fusion	private	
P38 [38]	2019	2D	WG	mono	T2W	axial	fusion	public	PROMISE12, NCI-ISBI 2013
P39 [39]	2019	2D	WG,CG	multi	T2W, CED	all	fusion	private	
P40 [40]	2019	3D	WG	mono	T2W	axial	fusion	public	PROMISE12
P41 [41]	2019	2D	CG,PZ	mono	T2W	axial	ERC	public	NCI-ISBI 2013
P42 [42]	2019	3D	WG	mono	T2W	axial	fusion	public	PROMISE12
P43 [43]	2019	3D	WG,CG,PZ	mono	T2W	axial	non-ERC	private	
P44 [44]	2019	3D	WG	mono	DCE	axial	undefined	private	
P45 [45]	2019	2D	WG	mono	T2W	axial	fusion	public	PROMISE12
P46 [46]	2019	2D	CG,PZ	mono	T2W	axial	ERC	public	PROSTATEx
P47 [47]	2019	3D	CG,PZ,AFS,DPU	mono	T2W	axial	ERC	public	PROSTATEx
P48 [48]	2019	3D	WG	mono	T2W	axial	fusion	public	PROMISE12
P49 [49]	2020	3D	WG,CG	mono	T2W	axial	fusion	private	
P50 [50]	2020	2D	WG,CG,PZ	mono	T2W	axial	ERC	private	
P51 [51]	2020	3D	WG	mono	T2W	axial	non-ERC	public	PROMISE12,Prostate-3T
P52 [52]	2020	2D	WG	mono	T2W	axial	fusion	fusion	
P53 [53]	2020	3D	WG	mono	T2W	axial	fusion	public	PROMISE12
P54 [54]	2020	3D	WG,PZ	mono	T2W	all	non-ERC	fusion	
P55 [55]	2020	2D	WG	mono	T2W	axial	fusion	public	PROMISE12, NCI-ISBI 2013
P56 [56]	2020	2D	WG	mono	T2W	axial	fusion	public	NCI-ISBI 2013, I2CVB
P57 [57]	2020	3D	WG	mono	T2W	axial	non-ERC	private	
P58 [58]	2020	2D	WG,CG,PZ	mono	T2W	axial	ERC	public	PROSTATEx
P59 [59]	2020	2D	CG,PZ	mono	T2W	axial	non-ERC	fusion	
P60 [60]	2020	3D	WG,TZ	mono	T2W	axial	non-ERC	private	
P61 [61]	2020	2D	WG	mono	T2W	axial	fusion	fusion	
P62 [62]	2020	2D	WG,CG,PZ	mono	T2W	axial	non-ERC	private	
P63 [63]	2020	3D	WG	mono	T2W	all	non-ERC	fusion	
P64 [64]	2020	2D	WG	mono	DWI	axial	non-ERC	private	
P65 [65]	2020	3D	WG	mono	T2W	axial	fusion	private	

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