Supplementary Table 1: A comparison between different approaches in literature from the point of view 1) author, 2) database used, 3) number of images used before and after augmentation in parenthesis, 4) the use of full image or ROI, 5) if pre-processing is done, 6) size of images used in pixel, 7) if augmentation is applied, 8) if it is end-to-end (E2E) technique, 9) if transfer learning (TL) is used, 10) muli-view (MV) or single-view (SV), 11) area under curve (AUC), 12) accuracy (Acc.%), 13) class used: normal images (NL); benign images (B); malignant (M); calcifications (MCs); architectural distortion (AD), 14) lesion being segmented, 15) number of layers in the architecture.

Author	**Year**	**Database**	**#Images**	**Kind**	**Pre-pro.**	**Size**	**AUG.**	**E2E**	**TL**	**View**	**AUC**	**Acc.%**	**Class**	**Lesion**	**Layers**
Lesion classification															
Sahiner [1]	1996	Private	168(672)	ROIs	Y	32×32	Y	N	N	SV	0.87	-	NL-Mass	Mass	3
Lo [2]	2002	MIAS	200(3,193)	ROIs	Y	512×512	Y	N	N	SV	0.89	-	NL-Mass	Mass	3
Domingues [3]	2013	INbreast	112	ROIs	N	32×32	N	N	N	SV	0.89	-	NL-Mass	Mass	3
Dhungel [4]	2015	BCRP, INbreast	116-77	ROIs	N	40×40	N	N	N	SV	0.9	-	NL-Mass	Mass	6
Kooi [5]	2016	Private	398(2.5M)	ROIs	Y	250×250	Y	N	N	SV	0.87		NL-Mass	Mass	11
Wichakam [6]	2016	INbreast	216(1,728)	ROIs	Y	32×32	Y	N	N	SV	-	98.4	NL-Mass	Mass	9
Zhu [7]	2017	INbreast	410	Image	Y	224×224	Y	Y	Y	MV	0.85	90	NL-Mass	Mass	8
Suzuki [8]	2016	DDSM	1,656	ROIs	Y	454×454	N	N	Y	SV	-	-	NL-Mass	Mass	8
Dubrovina [9]	2016	N/A	40(8k)	ROIs	Y	256×256	Y	N	N	SV	-	-	NL-Mass	Mass	7
Suzuki [10]	2016	DDSM	1,656	ROIs	Y	454×454	N	N	Y	SV	-	-	NL-Mass	Mass	8
Kooi [11]	2017	Private	398(2.5M)	ROIs	Y	250×250	Y	N	Y	MV	0.87	-	NL-Mass	Mass	22
Sun [12]	2017	Private	3158(25K)	ROIs	Y	52×52	Y	N	N	SV	0.88	82.2	NL-Mass	Mass	7
Samala [13]	2016	Private	2461(45072)	ROI	Y	128×128	Y	N	N	SV	0.99	-	NL-Mass	Mass	8
Hadad [14]	2017	Private	11092(32,064)	ROI	Y	32×32	Y	N	N	SV	0.94	87	NL-Mass	Mass	13
Chan [15]	1995	Private	52(1,744)	ROIs	Y	16×16	Y	N	N	SV	0.91	-	NL-MCs	MCs	3
Gardezi [16]	2017	IRMA	2795(25k)	ROIs, Image	Y	224×224	N	N	N	SV	1	100	NL-Mass	Mass	16
Ge [17]	2007	Private	192	ROIs	Y	16×16	Y	N	N	SV	0.96	-	NL-MCs	MCs	3
Valvano [18]	2017	Private	290(90,000)	ROIs	Y	99×99	Y	N	N	SV	-	83.7	NL-MCs	MCs	10
Mordang [19]	2016	Private	1606(45M)	ROIs	Y	13×13	Y	N	N	MV	-	-	NL-MCs	MCs	9
Wang [20]	2017	Private	840(1.94M)	ROIs	Y	95×95	Y	N	N	MV	-	-	NL-MCs	MCs	12
Bria [21]	2017	Private	7,579(≈27M)	ROIs	Y	12×12	Y	N	N	SV	-	-	NL-MCs	MCs	8
Ben-Ari [22]	2017	DDSM	136(21k)	ROIs	Y	224×224	Y	N	Y	MV	-	80	NL-AD	AD	9
Jamieson [23]	2012	Private	739(2,393)	ROIs	Y	140×140	Y	N	N	SV	0.71	-	B-M	Mass	4
Arevalo [24]	2015	INbreast	736(5,152)	ROIs	Y	150×150	Y	Y	Y	SV	0.82	-	B-M	Mass	7
Agarwal [25]	2015	DDSM	8752(50k)	ROIs	Y	64×64	Y	N	N	SV	-	90	B-M	Mass, MCs	8
Jiao [26]	2016	DDSM	600(1,800)	ROIs	Y	227×227	Y	N	Y	SV	-	96.7	B-M	Mass	9
Bekker [27]	2016	DDSM	1410	ROIs	N	N/A	N	N	N	SV	0.89	78.7	B-M	MCs	3
Sharma [28]	2016	DDSM	40	ROIs	Y	N/A	N	N	N	SV	0.85	79.2	B-M	Mass	N/A
Levy [29]	2016	DDSM	1820(36k)	ROIs	Y	224×224	Y	Y	N	SV	-	92.9	B-M	Mass	9
Abbas [30]	2016	MIAS, DDSM	600	ROIs	Y	250×250	N	Y	N	SV	0.91	91.5	B-M	Mass	N/A
Huynh [31]	2016	Private	607	ROIs	Y	256×256	N	N	Y	SV	0.86	-	B-M	Mass	8

Continuation of Table 1																
Author	**Year**	**Database**	**#Images**	**Kind**	**Pre-pro.**	**Size**	**AUG.**	**E2E**	**TL**	**View**	**AUC**	**Acc.%**	**Class**	**Lesion**	**Layers**
Lesion classification															
Arevalo [32]	2016	BCDR	736(5k)	ROIs	Y	150×150	Y	N	Y	SV	0.86	-	B-M	Mass	7
Jiang [33]	2017	BCDR	736(N/A)	ROIs	Y	227×227	Y	N	Y	SV	0.88	-	B-M	Mass	22
Samala [34]	2017	DDSM, Private	322(2576) 8334(17056)	ROI	Y	128×128	Y	N	Y	SV	0.82	-	B-M	Mass	10
Sert [35]	2017	DDSM	2620(5965)	ROIs	Y	224×224	Y	N	Y	SV	-	94.3	B-M	MCs	22
Jiao [36]	2017	DDSM	600(1,800)	ROIs	Y	227×227	Y	N	Y	SV	-	92.5	B-M	Mass	8
Jaffar [37]	2017	MIAS, DDSM.	2122(19k)	ROIs	Y	96×96	N	N	N	SV	0.93	93.4	B-M	Mass	8
Chougrad [38]	2017	BCDR	600(N/A)	ROIs	Y	299×299	Y	Y	Y	SV	0.96	97.5	B-M	Mass	221
Bakkouri [39]	2017	DDSM, BCDR.	10k(60k)	ROIs	Y	32×32	Y	N	N	SV	-	97.3	B-M	Mass	7
Antropova [40]	2017	Private	739	ROIs	Y	512×512	N	N	Y	SV	0.86	-	B-M	Mass	19
Qiu [41]	2017	Private	560	ROIs	Y	64×64	N	N	N	SV	0.79	-	B-M	Mass	8
Gallego [42]	2016	MIAS	322(600)	ROIs	Y	227×227	Y	N	Y	SV	-	64.5	NL-B-M	Mass	8
Jadoon [43]	2017	IRMA	2796 (19k)	ROIs	Y	28×28	Y	N	N	SV	-	83.7	NL-B-M	Mass	5
Yi [44]	2017	DDSM	2085(N/A)	ROIs	Y	224×224	Y	N	Y	MV	0.91	85	NL-B-M	Mass	22
Teare [45]	2017	DDSM, ZMDS	>6000(N/A) 1739(N/A)	Image	Y	299×299	Y	N	Y	SV	0.92	-	NL-B-M	Mass, MCs	22
Hepsaug [46]	2017	MIAS, BCDR	1160-2474	ROIs	Y	50×50	N	N	N	SV	-	68, 62	NL-B-M	Mass, MCs	N/A
Hang [47]	2017	DDSM	1318	Image	Y	521×521	N	N	N	MV	-	66	NL-B-M	Mass	13
Kooi [48]	2017	Private	490	ROIs	Y	250×250	N	N	N	SV	0.87	-	Mass-MCs	Mass, MCs	N/A
Qiu [49]	2016	N/A	560	ROIs	Y	512×512	N	Y	N	SV	0.8	-	B-M	Mass	8
Dhungel [50]	2016	INbreast	116(1160)	ROIs	Y	40×40	Y	Y	Y	SV	-	84	B-M	Mass	5
Geras [51]	2017	Private	102,800	Image	Y	$2k \times 2k$	N	Y	N	MV	0.76	-	NL-M	Mass, MCs	11
Kooi [52]	2017	Private	44K(1.3M)	ROIs	Y	250×250	Y	Y	N	SV	0.94	-	NL-M, B-M	Mass	7
Dhungel [53]	2017	INbreast	512	Image	Y	120×120	Y	Y	Y	MV	0.8	-	NL-B-M	Mass, MCs	392
Lotter [54]	2017	DDSM	10480(N/A)	Image	Y	256×256	Y	Y	Y	MV	0.92	-	NL-B-M	Mass, MCs	152
Ribli [55]	2017	DDSM, INbreast	26020(N/A), 115	Image	Y	$2.1k$×$1.7k$	Y	Y	N	SV	0.95	-	NL-B-M	Mass, MCs	16
Akselrod [56]	2017	Private	860	Image	Y	224×224	N	Y	Y	SV	0.72	77	NL-B-M	Mass	16
Carneiro [57]	2015	DDSM, INbreast	680-410	Image	Y	264×264	N	Y	Y	MV	0.97	-	B-M	Mass	8
Carneiro [58]	2017	DDSM, INbreast	680-410	Image	Y	264×264	N	N	Y	MV	0.99-0.91	-	NL-B-M	Mass, MCs	8
Kooi [59]	2017	Private	201,851(N/A)	ROIs	Y	250×250	Y	N	N	MV	0.88	-	NL-Mass	Mass	19
Lesion localization															
Ertosun [60]	2015	DDSM	2420(1.8M)	ROIs	Y	256×256	Y	Y	Y	SV	-	85	NL-Mass	Mass	22
Hwang [61]	2016	MIAS, DDSM	15,837	Image	Y	500×500	N	N	N	SV	0.89	84.1	NL-Mass	Mass	7

Continuation of Table 1

Author	Year	Database	#Images	Kind	Pre-pro.	Size	AUG.	E2E	TL	View	AUC	Acc.%	Class	Lesion	Layers
Lesion localization															
Akselrod [62]	2016	Private	850(4,75)	Image	N	800×800	Y	Y	N	SV	-	-	NL-B-M	Mass, MCs	16
Carneiro [63]	2016	BCRP, INbreast	316(3,160), 410(4.1k)	ROIs	Y	40×40	Y	Y	N	SV	-	-	NL-B-M	Mass	8
Choukroun [64]	2017	Private	2,500(28k)	ROIs	Y	224×224	Y	N	Y	SV	0.83	-	NL-B-M	Mass, MCs	8
Zhu [65]	2016	BCRP, INbreast	171(680), 116(464)	ROIs	Y	40×40	Y	Y	N	SV	-	91.3	NL-M	Mass	4
Dhungel [66]	2017	INbreast	410(4.1k)	ROIs	Y	40×40	Y	Y	Y	SV	0.76	91	B-M	Mass	5
Kisilev [67]	2016	DDSM	512	ROIs	Y	128×128	N	N	N	SV	-	-	B-M	Mass	7
Al-masni [68]	2017	DDSM	600	Image	Y	448×448	N	N	Y	SV	0.87	85.5	B-M	Mass	27
Platania [69]	2017	IRMA	10,480(25k)	ROIs, Image	Y	128×128	Y	Y	Y	SV	0.92	93.5	B-M	Mass	19
Sun [70]	2016	Private	420(42k)	ROIs	Y	52×52	N	N	N	MV	0.72	-	B-M	Mass	8
Risk assessment															
Qiu [71]	2016	Private	270	ROIs	Y	256×256	N	N	N	SV	-	71.4	BI-RADS	Density	8
Fonseca [72]	2015	Private	729	Image	N	200×200	N	N	N	SV	-	73	BI-RADS	Density	3
Fonseca [73]	2016	Private	1060(N/A)	Image	Y	200×200	Y	N	Y	SV	-	-	BI-RADS	Density	3
Becker [74]	2017	BCDR	286(N/A)	Image	Y	N/A	Y	Y	N	SV	0.81	-	BI-RADS	Density	N/A
Kallenberg [75]	2016	Private	1,555	ROIs	Y	24×24	N	N	N	SV	-	59	BI-RADS	Density	6
Ahn [76]	2017	Private	10,94(N/A)	ROIs	Y	41×41	Y	N	N	SV	-	-	BI-RADS	Density	16
Li [77]	2017	Private	661(1M)	ROIs	Y	61×61	Y	N	N	SV	-	-	BI-RADS	Density	6
Wu [78]	2017	Private	201,179(N/A)	Image	Y	2.6k×2k	Y	Y	Y	MV	0.93	-	BI-RADS	Density	19
Thomaz [79]	2017	Private	307	Image	Y	260×200	N	N	N	SV	-	98.4	BI-RADS	Density	N/A
Mohamed [80]	2017	Private	15,415	Image	Y	227×227	N	N	N	SV	0.92	-	BI-RADS	Density	8
Mohamed [81]	2017	Private	6000	Image	Y	227×227	N	N	Y	SV	0.98	-	BI-RADS	Density	8
Image retrieval															
Qayyum [82]	2017	Multiple	7200	Image	Y	224×224	N	Y	N	SV	-	99.8	24 classes	All	8
Ahmad [83]	2017	IRMA	15363(68k)	ROIs	Y	224×224	Y	Y	Y	SV	0.75	-	193 classes	All	16
Resolution image reconstruction															
Umehara [84]	2017	CBIS-DDSM	711	Image	Y	variable	Y	Y	N	SV	-	-	Same image	Any	23

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