Supplementary Online Content

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This supplementary material has been provided by the authors to give readers additional information about their work.

eTable 1: General characteristics of all included studies (n=132)

NMLs = non-melanocytic lesions, nr= not reported, SVM= support vector machine, ANN= artificial neural network, *histopathology was only used for suspicious lesions

STUDY ID	METHOD	TEST SET SOURCE	TOTAL DATA SET SIZE	# OF MELANOMA	NMLS INCLUDED	CLASSIFIER	INDEPENDENT TEST SET	GOLD STANDARD FOR THE TEST SET	INCLUDED IN QUANTITATIVE ANALYSIS
ABUZAGHLEH 2015[1]	computer vision	public	200	40	no	SVM	no	histopathology*, dermatoscopy	
AFIFI 2017[2]	computer vision	public	356	168	nr	SVM	no	nr	
AMOABEDINI 2018[3]	computer vision	public	76	38	no	threshold	no	nr	Yes
ASCIERTO 2010[4]	hardware-based	proprietary	54	12	no	nr	yes	histopathology	Yes
BARATA 2015A[5]	computer vision	public	482	241	nr	ensemble classifier	no	expert consensus	
BARATA 2015B[6]	computer vision	public	200	40	no	random forests	no	histopathology*, dermatoscopy	Yes
BARROS MENDES 2018[7]	deep learning	public	5286	374	yes	ANN	no	nr	
BARZEGARI 2005[8]	computer vision	proprietary	122	6	yes	ANN	no	histopathology	Yes
BAUR 2018[9]	deep learning	public	2000	2000	yes	ANN	no	histopathology*, expert consensus	
BHATTACHARYA 2017[10]	deep learning	public	275	128	no	SVM	no	nr	
BI 2017[11]	deep learning	public	4350	nr	nr	ANN	yes	histopathology*, expert consensus	Yes
BISSOTO 2018[12]	deep learning	public	nr	nr	yes	ANN	yes	nr	
BONO 2002[13]	hardware-based	proprietary	313	66	yes	discriminant analysis	yes	histopathology	
CARCAGNI 2018[14]	deep learning	public	10015	1113	yes	ANN	yes	histopathology*, follow-up, confocal microscopy, expert consensus	
CELEBI 2007[15]	computer vision	public	596	88	yes	SVM	no	histopathology*, follow-up	
CELEBI 2008[16]	computer vision	public	545	186	yes	decision tree	no	histopathology*, follow-up	
CHAKRAVATI 2015[17]	computer vision	public	456	251	nr	ANN	no	histopathology*, clinical evaluation	

CHANG H 2017[18]	deep learning	public	2750	521	yes	ANN	yes	histopathology*, expert consensus	Yes
CHANG WY 2013[19]	computer vision	proprietary	769	8	yes	SVM	no	histopathology	
CHANG WY 2015[20]	computer vision	proprietary	347	7	yes	SVM	yes	histopathology	
CHOU 2017[21]	deep learning	public	200	40	no	SVM	no	histopathology*, dermatoscopy	
CODELLA 2016[22]	deep learning	public	1279	248	no	SVM	yes	histopathology*, expert consensus, nr for part of the lesions	Yes
CODELLA 2018[23]	deep learning	public	2750	521	yes	kNN	no	histopathology*, expert consensus	
DEL ROSARIO 2018[24]	computer vision	proprietary	1076	71	yes	threshold	yes	histopathology	Yes
DING 2015[25]	hardware-based	proprietary	46	12	yes	SVM	no	nr	Yes
DO 2014[26]	computer vision	proprietary	81	29	nr	SVM	no	nr	
DO 2017[27]	computer vision	proprietary	184	67	no	SVM	no	histopathology*, expert consensus	Yes
DREISEITL 2009[28]	computer vision	proprietary	3827	31	no	ANN	yes	histopathology*, follow-up	Yes
ESTEVA 2017[29]	deep learning	proprietary	129450	nr	yes	ANN	no	test set histopathology, rest unspecified (dermatologist-labelled)	
FERRI 2010[30]	computer vision	proprietary	977	50	no	SVM	no	histopathology*, follow-up	Yes
FINK 2016[31]	hardware-based	proprietary	360	3	no	threshold	yes	histopathology*, dermoscopy follow-up	Yes
FORNACIALI 2016[32]	deep learning	public	1052	267	nr	SVM	no	histopathology*, clinical evaluation	
FORSCHNER 2018[33]	hardware-based	proprietary	529	101	yes	ANN	no	histopathology	Yes
FRIEDMAN 2008[34]	hardware-based	proprietary	99	49	no	threshold	no	histopathology	
GAREAU 2017[35]	computer vision	proprietary	120	60	no	decision tree	no	histopathology	Yes
GARNAVI 2012[36]	computer vision	proprietary	289	114	nr	random forests	no	nr	Yes
GAUTAM 2018[37]	computer vision	public	294	138	nr	random forests	no	nr	Yes

GILMORE 2009[38]	computer vision	proprietary	312	102	no	nr	no	histopathology*, dermatoscopy	
GILMORE 2010[39]	computer vision	proprietary	199	101	no	SVM	no	histopathology	Yes
GILMORE 2018[40]	computer vision	proprietary	250	85	no	SVM	no	histopathology*, dermoscopy evaluation	
GONZALEZ DIAZ 2017[41]	deep learning	public	2750	521	yes	ANN	yes	histopathology*, expert consensus	Yes
GOYAL 2018[42]	deep learning	public	10015	1113	yes	ANN	yes	histopathology*, follow-up, confocal microscopy, expert consensus	
GUO S 2017[43]	deep learning	public	2750	521	yes	ensemble classifier	yes	histopathology*, expert consensus	Yes
GUO Y 2018[44]	deep learning	public	10015	1113	yes	ANN	yes	histopathology*, follow-up, confocal microscopy, expert consensus	
HAENSSLE 2018[45]	deep learning	proprietary	>100000	nr	no	ANN	no	histopathology*, dermoscopy follow-up	Yes
HAIDER 2014[46]	computer vision	public	206	119	nr	bayesian	no	histopathology	Yes
HARANGI 2017[47]	deep learning	public	2750	521	yes	ANN	yes	histopathology*, expert consensus	Yes
HARANGI 2018[48]	deep learning	public	2750	521	yes	ensemble on ANNs	no	histopathology*, expert consensus	
HARDIE 2018[49]	computer vision	public	10015	1113	yes	SVM	no	histopathology*, follow-up, confocal microscopy, expert consensus	Yes
HAR-SHAI 2005[50]	hardware-based	proprietary	449	69	yes	threshold	yes	histopathology	Yes
HAUSCHILD 2014[51]	hardware-based	proprietary	130	65	yes	threshold	yes	histopathology	
HUNGER 2012[52]	hardware-based	proprietary	45	12	no	threshold	yes	histopathology*, follow-up	
JAWOREK-KORJAKOWSKA 2016A[53]	computer vision	public	300	60	no	SVM	no	histopathology	Yes
JAWOREK-KORJAKOWSKA 2016B[54]	computer vision	public	200	70	nr	SVM	no	histopathology	
JIJI 2017[55]	computer vision	public	2750	521	yes	SVM	yes	histopathology*, expert consensus	Yes
KAUR 2015[56]	computer vision	proprietary	192	114	no	linear regression	no	histopathology*, follow-up	

KAWAHARA 2018[57]	deep learning	proprietary	1011	252	yes	ANN	no	nr	Yes
KHAN 2018[58]	computer vision	public	4752	1057	yes	SVM	no	histopathology*, follow-up, expert consensus, unknown for partof the lesions	Yes
KITADA 2018[59]	deep learning	public	10015	1113	yes	ANN	yes	histopathology*, follow-up, confocal microscopy, expert consensus	
KOSTOPOULOS 2017[60]	computer vision	public	399	69	no	ANN	no	nr	Yes
LAI 2018[61]	deep learning	public	2000	374	yes	ANN	no	histopathology*, expert consensus	
LEE 2018[62]	deep learning	public	10015	1113	yes	ANN	yes	histopathology*, follow-up, confocal microscopy, expert consensus	
LI K 2018[63]	deep learning	public	10015	1113	yes	ANN	no	histopathology*, follow-up, confocal microscopy, expert consensus	Yes
LI L 2014[64]	hardware-based	public	187	19	no	bayesian	no	histopathology	
LI Y 2017[65]	deep learning	public	2750	521	yes	ANN	yes	histopathology*, expert consensus	Yes
LINGALA 2014[66]	computer vision	proprietary	888	195	no	logistic regression model	no	nr	
LIU 2015[67]	computer vision	public	258	76	yes	SVM	no	histopathology*, clinical evaluation	Yes
LU 2018[68]	deep learning	public	10015	1113	yes	ANN	no	histopathology*, follow-up, confocal microscopy, expert consensus	
MAGLIOGIANNIS 2004[69]	computer vision	proprietary	17	7	no	SVM	no	histopathology	
MAGLIOGIANNIS 2015[70]	computer vision	proprietary	208	100	no	SVM	no	histopathology	Yes
MAHBOD 2017[71]	deep learning	public	2750	521	yes	SVM	yes	histopathology*, expert consensus	Yes
MAITNER 2018[72]	deep learning	public	10015	1113	yes	ANN	yes	histopathology*, follow-up, confocal microscopy, expert consensus	
MALVEHY 2014[73]	hardware-based	proprietary	2416	265	yes	threshold	yes	histopathology	Yes
MANOUSAKI 2006[74]	computer vision	proprietary	132	23	no	logistic regression model	no	histopathology	Yes
MARCHETTI 2018[75]	deep learning	public	379	75	no	threshold	no	histopathology*, expert consensus	Yes
MARQUES 2012[76]	computer vision	proprietary	163	17	no	nr	no	nr	Yes

MATSUNAGA 2017[77]	deep learning	public	4194	930	yes	ANN	yes	histopathology*, expert consensus	Yes
MENEGOLA 2016[78]	deep learning	public	nr	nr	yes	SVM	no	histopathology	
MENEGOLA 2017A[79]	deep learning	public	nr	nr	yes	SVM	no	histopathology*, expert consensus, nr for part of the lesions	Yes
MENEGOLA 2017B[80]	deep learning	public	18000	nr	yes	SVM	yes	nr	Yes
MESSADI 2009[81]	computer vision	proprietary	180	72	no	ANN	no	clinical evaluation	
MIRUNALINI 2017[82]	deep learning	public	2750	521	yes	ANN	yes	histopathology*, expert consensus	Yes
MOLLERSEN 2015[83]	computer vision	proprietary	877	45	yes	nr	yes	histopathology	Yes
MONHEIT 2011[84]	hardware-based	proprietary	1632	127	yes	threshold	yes	histopathology	
MUNIA 2017[85]	computer vision	public	170	70	no	SVM	no	nr	Yes
MURPHREE 2017[86]	deep learning	public	2750	521	yes	ANN	yes	histopathology*, expert consensus	Yes
NADER VASCONCELOS 2017[87]	deep learning	public	2750	521	yes	ANN	yes	histopathology*, expert consensus	Yes
NANNI 2018[88]	deep learning	public	10015	1113	yes	ANN	yes	histopathology*, follow-up, confocal microscopy, expert consensus	
NASIRI 2018[89]	deep learning	public	10015	1113	yes	ANN	yes	histopathology*, follow-up, confocal microscopy, expert consensus	
NASR-ESFAHANI 2016[90]	deep learning	public	170	70	no	ANN	yes	nr	
NICOLAS 2014[91]	computer vision	proprietary	150	nr	yes	kNN	no	histopathology	
PAL 2018[92]	deep learning	public	10015	1113	yes	ANN	yes	histopathology*, follow-up, confocal microscopy, expert consensus	
PATWARDHAN 2005[93]	hardware-based	proprietary	90	30	no	bell membership function	no	histopathology	Yes
PELLACANI 2004[94]	computer vision	proprietary	339	113	no	discriminant analysis	no	histopathology	Yes
PEREZ 2018[95]	deep learning	public	2750	512	yes	ANN	no	histopathology*, expert consensus	
PICCOLO 2014[96]	computer vision	proprietary	165	33	no	threshold	no	histopathology	Yes

POLAP 2018[97]	computer vision	public	200	40	no	ANN	no	histopathology*, dermoscopy evaluation	Yes
QUINZAN 2013[98]	hardware-based	proprietary	32	7	no	qualified majority voting with 5 SVMs	no	histopathology	Yes
RADHAKRISHNAN 2017[99]	deep learning	public	1279	248	no	ANN	no	histopathology*, expert consensus, nr for part of the lesions	Yes
RADHAKRISHNAN 2018[100]	deep learning	public	2750	512	yes	ANN	no	histopathology*, expert consensus	
RAMEZANI 2014[101]	computer vision	public	282	133	nr	SVM	no	nr	Yes
RAY 2018[102]	deep learning	public	10015	1113	yes	deep forest	no	histopathology*, follow-up, confocal microscopy, expert consensus	
REZVANTALAB 2018[103]	deep learning	public	10135	1153	yes	ANN	no	histopathology*, follow-up, confocal microscopy, expert consensus, dermoscopy evaluation	Yes
ROCHA 2017[104]	hardware-based	proprietary	160	6	no	threshold	yes	histopathology*, follow-up	Yes
RUBEGNI 2015[105]	computer vision	proprietary	856	272	no	logistic regression model	no	histopathology	Yes
RUIZ 2008[106]	computer vision	public	110	nr	nr	voting system based on ANNs and a bayesian classifier	no	nr	
SABBAGHI 2018[107]	computer vision	proprietary	825	181	no	SVM	no	histopathology*, dermoscopy follow-up	
SATHEESHA 2017[108]	computer vision	public	263	nr	no	SVM	no	nr	
SBONER 2003[109]	computer vision	proprietary	152	42	no	ensemble classifier	no	histopathology	Yes
SHAIFIEE 2017[110]	deep learning	public	9152	567	yes	ANN	no	histopathology	
SITU 2008[111]	computer vision	proprietary	100	30	no	SVM	no	nr	
SITU 2010[112]	computer vision	proprietary	100	30	no	SVM	no	nr	Yes
SITU 2011[113]	computer vision	public	360	90	nr	SVM	no	histopathology	
STANLEY 2007[114]	computer vision	public	226	113	no	threshold	no	histopathology	Yes
STOECKER 2005[115]	computer vision	proprietary	512	165	no	ANN	no	histopathology	

SWANSON 2010[116]	computer vision	proprietary	118	11	yes	threshold	no	histopathology	Yes
TEIXEIRA SOUSA 2017[117]	deep learning	public	2750	521	yes	ANN	yes	histopathology*, expert consensus	Yes
TENENHAUS 2010[118]	computer vision	proprietary	227	32	no	partial least squares model	no	histopathology*, clinical evaluation	Yes
TOMATIS 2003[119]	hardware-based	proprietary	573	132	yes	ANN	no	histopathology	
TOMATIS 2005[120]	hardware-based	proprietary	2507	184	yes	ANN	no	histopathology*, clinical evaluation	
TSCHANDL 2018[121]	deep learning	public	20329	3044	yes	ANN	no	histopathology*, expert consensus, nr for part of the lesions	Yes
VALLE 2017[122]	deep learning	public	19931	2401	yes	ANN	no	nr	
WADHAWAN 2011[123]	computer vision	public	347	110	nr	SVM	no	dermatoscopy	Yes
WOLF 2013[124]	computer vision	proprietary	188	60	yes	nr	yes	histopathology	Yes
WU 2018[125]	deep learning	public	10015	1113	yes	ANN	no	histopathology*, follow-up, confocal microscopy, expert consensus	
YANG 2017[126]	deep learning	public	2750	521	yes	ANN	yes	histopathology*, expert consensus	Yes
YAP 2018[127]	deep learning	proprietary	2917	727	yes	ANN	no	histopathology	Yes
YI 2018[128]	deep learning	public	1479	288	no	ANN	no	histopathology*, dermoscopy evaluation, expert consensus	
YU C 2018[129]	deep learning	proprietary	724	350	no	ANN	no	histopathology	Yes
YU L 2017[130]	deep learning	public	1279	248	no	ANN	no	histopathology*, expert consensus, nr for part oft he lesions	Yes
ZEKOVIC 2014[131]	hardware-based	proprietary	48	11	yes	partial least squares model	no	histopathology	
ZHOU 2011[132]	hardware-based	proprietary	76	23	nr	ensemble classifier	no	nr	

eTable 2: Assessment of bias risk (br) and applicability concerns (ap) of the included studies (n=132) using the QUADAS-2 tool.

STUDY ID	SAMPLE SELECTION (BR)	INDEX TEST (BR)	REFERENCE STANDARD (BR)	FLOW AND TIMING (BR)	SAMPLE SELECTION (AP)	INDEX TEST (AP)	REFERENCE STANDARD (AP)
ABUZAGHLEH 2015[1]	high	high	low	low	low	low	low
AFIFI 2017[2]	high	high	moderate	high	low	low	low
AMOABEDINI 2018[3]	high	high	moderate	high	low	low	low
ASCIERTO 2010[4]	low	low	low	low	low	low	low
BARATA 2015A[5]	high	high	low	low	low	low	low
BARATA 2015B[6]	high	high	low	low	low	low	low
BARROS MENDES 2018[7]	high	high	moderate	high	low	low	low
BARZEGARI 2005[8]	low	high	low	low	low	low	low
BAUR 2018[9]	high	high	low	low	low	low	low
BHATTACHARYA 2017[10]	high	high	moderate	moderate	low	low	low
BI 2017[11]	high	low	moderate	low	low	low	low
BISSOTO 2018[12]	high	low	moderate	low	moderate	moderate	low
BONO 2002[13]	high	low	low	low	moderate	moderate	low
CARCAGNI 2018[14]	high	low	low	low	moderate	moderate	low
CELEBI 2007[15]	high	high	low	high	low	low	low
CELEBI 2008[16]	high	high	low	low	moderate	moderate	low
CHAKRAVATI 2015[17]	high	high	moderate	high	low	low	low
CHANG H 2017[18]	high	low	moderate	low	low	low	moderate
CHANG WY 2013[19]	high	high	low	low	moderate	moderate	low
CHANG WY 2015[20]	high	high	low	low	moderate	moderate	low
CHOU 2017[21]	high	high	low	low	low	low	low
CODELLA 2016[22]	high	high	high	low	low	low	low
CODELLA 2018[23]	high	high	low	low	low	low	low
DEL ROSARIO 2018[24]	high	high	low	high	low	low	low
DING 2015[25]	high	high	moderate	moderate	low	low	moderate
DO 2014[26]	high	high	moderate	moderate	moderate	low	moderate

DO 2017[27]	high	high	low	low	low	low	low
DREISEITL 2009[28]	low	low	low	high	low	low	low
ESTEVA 2017[29]	high	low	low	low	low	low	low
FERRI 2010[30]	high	low	low	low	low	low	low
FINK 2016[31]	high	low	high	high	low	low	low
FORNACIALI 2016[32]	high	high	low	low	low	low	low
FORSCHNER 2018[33]	high	low	low	low	moderate	moderate	low
FRIEDMAN 2008[34]	high	low	low	low	moderate	moderate	low
GAREAU 2017[35]	high	high	low	high	low	low	low
GARNAVI 2012[36]	high	high	high	moderate	low	low	moderate
GAUTAM 2018[37]	high	high	moderate	moderate	low	low	low
GILMORE 2009[38]	high	high	high	low	low	low	low
GILMORE 2010[39]	high	high	low	low	low	low	low
GILMORE 2018[40]	high	high	low	low	low	low	low
GONZALEZ DIAZ 2017[41]	high	low	low	low	low	low	low
GOYAL 2018[42]	high	low	low	low	moderate	moderate	low
GUO S 2017[43]	high	low	low	low	low	low	low
GUO Y 2018[44]	high	low	low	low	moderate	moderate	low
HAENSSLE 2018[45]	high	low	low	low	low	low	low
HAIDER 2014[46]	high	high	low	low	low	low	low
HARANGI 2017[47]	high	low	low	low	low	low	low
HARANGI 2018[48]	high	high	low	low	low	low	low
HARDIE 2018[49]	high	high	low	low	moderate	moderate	low
HAR-SHAI 2005[50]	low	low	low	high	low	low	low
HAUSCHILD 2014[51]	high	low	low	low	moderate	moderate	low
HUNGER 2012[52]	low	low	low	low	low	low	low
JAWOREK-KORJAKOWSKA 2016A[53]	high	high	low	low	low	low	low
JAWOREK-KORJAKOWSKA 2016B[54]	high	high	low	low	low	low	low
JIJI 2017[55]	high	low	low	low	low	low	low
KAUR 2015[56]	high	high	low	low	low	low	low

KAWAHARA 2018[57]	high	high	moderate	low	moderate	moderate	low
KHAN 2018[58]	high	high	moderate	moderate	low	low	low
KITADA 2018[59]	high	low	low	low	moderate	moderate	low
KOSTOPOULOS 2017[60]	high	low	moderate	low	low	low	low
LAI 2018[61]	high	high	low	low	low	low	low
LEE 2018[62]	high	low	low	low	moderate	moderate	low
LI K 2018[63]	high	high	low	low	moderate	moderate	low
LI L 2014[64]	high	high	low	low	low	low	low
LI Y 2017[65]	high	low	low	low	low	low	low
LINGALA 2014[66]	high	high	low	low	low	low	low
LIU 2015[67]	high	low	high	low	low	low	low
LU 2018[68]	high	high	low	low	moderate	moderate	low
MAGLIOGIANNIS 2004[69]	high	high	low	low	low	low	low
MAGLIOGIANNIS 2015[70]	high	high	low	low	low	low	low
MAHBOD 2017[71]	high	low	low	low	low	low	low
MAITNER 2018[72]	high	low	low	low	moderate	moderate	low
MALVEHY 2014[73]	low	low	low	low	moderate	moderate	low
MANOUSAKI 2006[74]	high	high	low	low	low	low	low
MARCHETTI 2018[75]	high	high	low	low	low	low	low
MARQUES 2012[76]	high	low	low	low	low	low	low
MATSUNAGA 2017[77]	high	low	low	low	low	low	low
MENEGOLA 2016[78]	high	high	low	low	low	low	low
MENEGOLA 2017A[79]	high	high	low	low	low	low	low
MENEGOLA 2017B[80]	high	low	low	low	low	low	low
MESSADI 2009[81]	high	high	high	low	low	low	low
MIRUNALINI 2017[82]	high	low	low	low	low	low	low
MOLLERSEN 2015[83]	low	low	low	low	moderate	moderate	low
MONHEIT 2011[84]	high	low	low	high	moderate	moderate	low
MUNIA 2017[85]	high	high	moderate	low	low	low	low
MURPHREE 2017[86]	high	low	low	low	low	low	low
NADER VASCONCELOS 2017[87]	high	low	low	low	low	low	low

NANNI 2018[88]	high	low	low	low	moderate	moderate	low
NASIRI 2018[89]	high	low	low	low	moderate	moderate	low
NASR-ESFAHANI 2016[90]	high	high	moderate	low	low	low	low
NICOLAS 2014[91]	high	high	low	low	low	low	low
PAL 2018[92]	high	low	low	low	moderate	moderate	low
PATWARDHAN 2005[93]	high	high	low	low	low	low	low
PELLACANI 2004[94]	high	high	low	low	low	low	low
PEREZ 2018[95]	high	high	low	low	low	low	low
PICCOLO 2014[96]	high	low	low	low	low	low	low
POLAP 2018[97]	high	high	low	low	low	low	low
QUINZAN 2013[98]	low	high	low	low	low	low	low
RADHAKRISHNAN 2017[99]	high	high	high	low	low	low	low
RADHAKRISHNAN 2018[100]	high	high	low	low	low	low	low
RAMEZANI 2014[101]	high	high	moderate	moderate	low	low	low
RAY 2018[102]	high	high	low	low	moderate	moderate	low
REZVANTALAB 2018[103]	high	high	low	low	moderate	moderate	low
ROCHA 2017[104]	low	low	low	low	low	low	low
RUBEGNI 2015[105]	high	high	low	low	low	low	low
RUIZ 2008[106]	high	high	moderate	moderate	low	low	low
SABBAGHI 2018[107]	high	high	low	low	low	low	low
SATHEESHA 2017[108]	high	high	moderate	low	low	low	low
SBONER 2003[109]	high	high	low	low	low	low	low
SHAIFIEE 2017[110]	high	low	low	low	moderate	moderate	low
SITU 2008[111]	high	high	moderate	low	low	low	moderate
SITU 2010[112]	high	high	moderate	low	low	low	moderate
SITU 2011[113]	high	low	low	low	low	low	low
STANLEY 2007[114]	high	high	low	low	low	low	low
STOECKER 2005[115]	high	low	low	low	low	low	low
SWANSON 2010[116]	low	high	low	low	low	low	low
TEIXEIRA SOUSA 2017[117]	high	low	low	low	low	low	low
TENENHAUS 2010[118]	high	low	moderate	high	low	low	low

TOMATIS 2003[119]	low	high	low	low	low	low	low
TOMATIS 2005[120]	high	low	low	low	low	low	low
TSCHANDL 2018[121]	high	high	low	low	low	low	low
VALLE 2017[122]	high	low	high	low	low	low	low
WADHAWAN 2011[123]	high	low	high	low	low	low	low
WOLF 2013[124]	high	low	low	low	low	low	low
WU 2018[125]	high	high	low	low	moderate	moderate	low
YANG 2017[126]	high	low	low	low	low	low	low
YAP 2018[127]	high	high	low	low	moderate	moderate	low
YI 2018[128]	high	high	low	low	low	low	low
YU C 2018[129]	high	high	low	low	low	low	low
YU L 2017[130]	high	low	high	low	low	low	low
ZEKOVIC 2014[131]	high	low	low	low	low	low	low
ZHOU 2011[132]	high	high	moderate	moderate	low	low	low

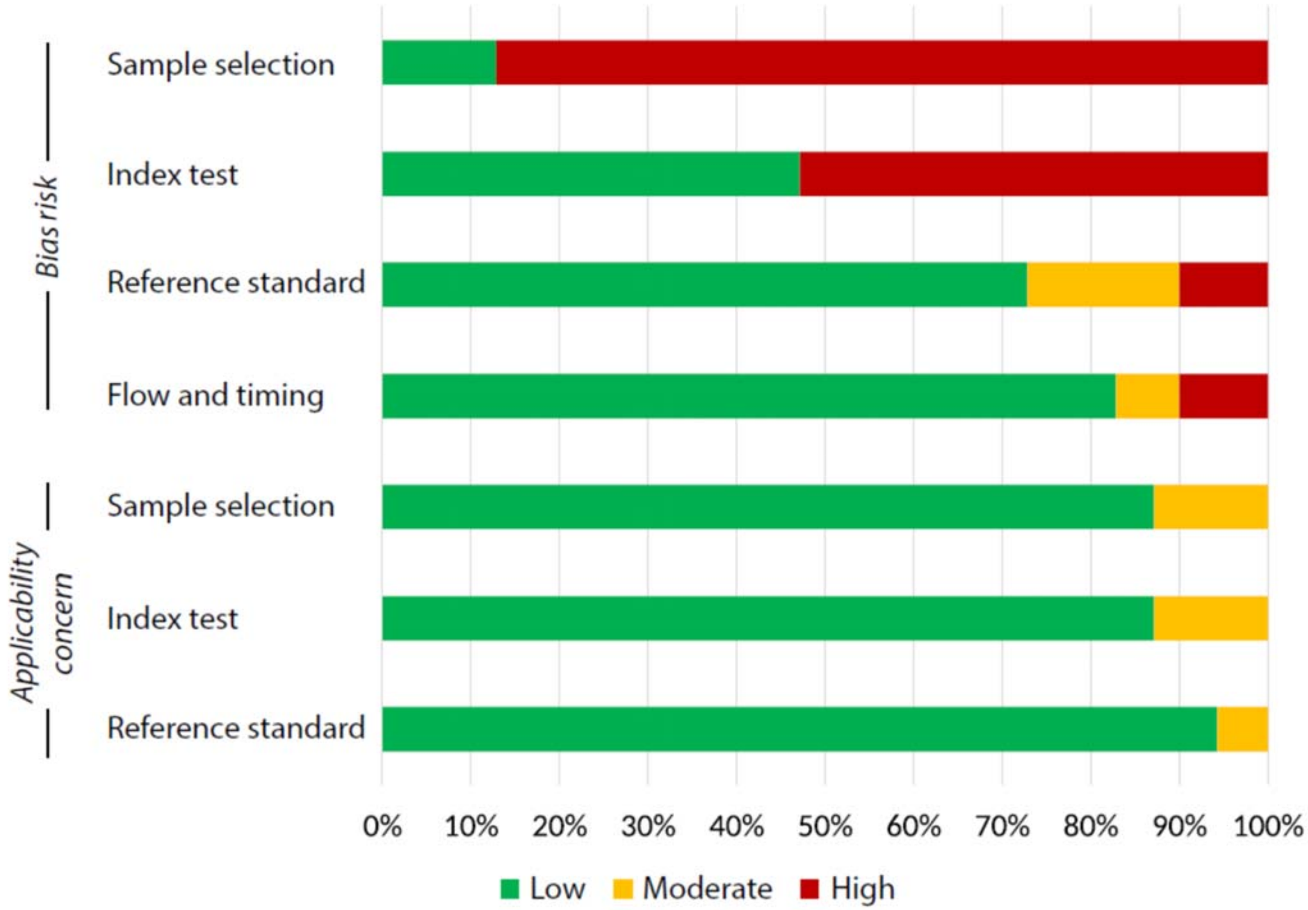
eTable3: Sensitivity, specificy and covariable effects calculated with two identified outliers (Wolf 2013[124] and Jiji 2017[55]) excluded.

			Summary Estimate with 95% CI	Univariate p-value
Overall		Sensitivity	0.74 (0.66-0.81)	
		Specificity	0.85 (0.80-0.89)	
Dataset Independence	Independent	Sensitivity	0.51 (0.32-0.70)	
		Specificity	0.85 (0.74-0.92)	
	Non-Independent	Sensitivity	0.82 (0.77-0.86)	p<0.001
		Specificity	0.85 (0.80-0.88)	p=0.967
Dataset Public	Public	Sensitivity	0.57 (0.44-0.69)	
		Specificity	0.92 (0.88-0.94)	
	Proprietary	Sensitivity	0.87 (0.83-0.91)	p<0.001
		Specificity	0.73 (0.64-0.80)	p<0.001
CAD Method	Computer Vision	Sensitivity	0.86 (0.82-0.89)	
		Specificity	0.79 (0.71-0.85)	
	Deep Learning	Sensitivity	0.44 (0.30-0.59)	p<0.001*
		Specificity	0.92 (0.89-0.95)	p<0.001*
	Hardware Based	Sensitivity	0.86 (0.77-0.92)	p=0.899*
		Specificity	0.70 (0.54-0.82)	p=0.352*

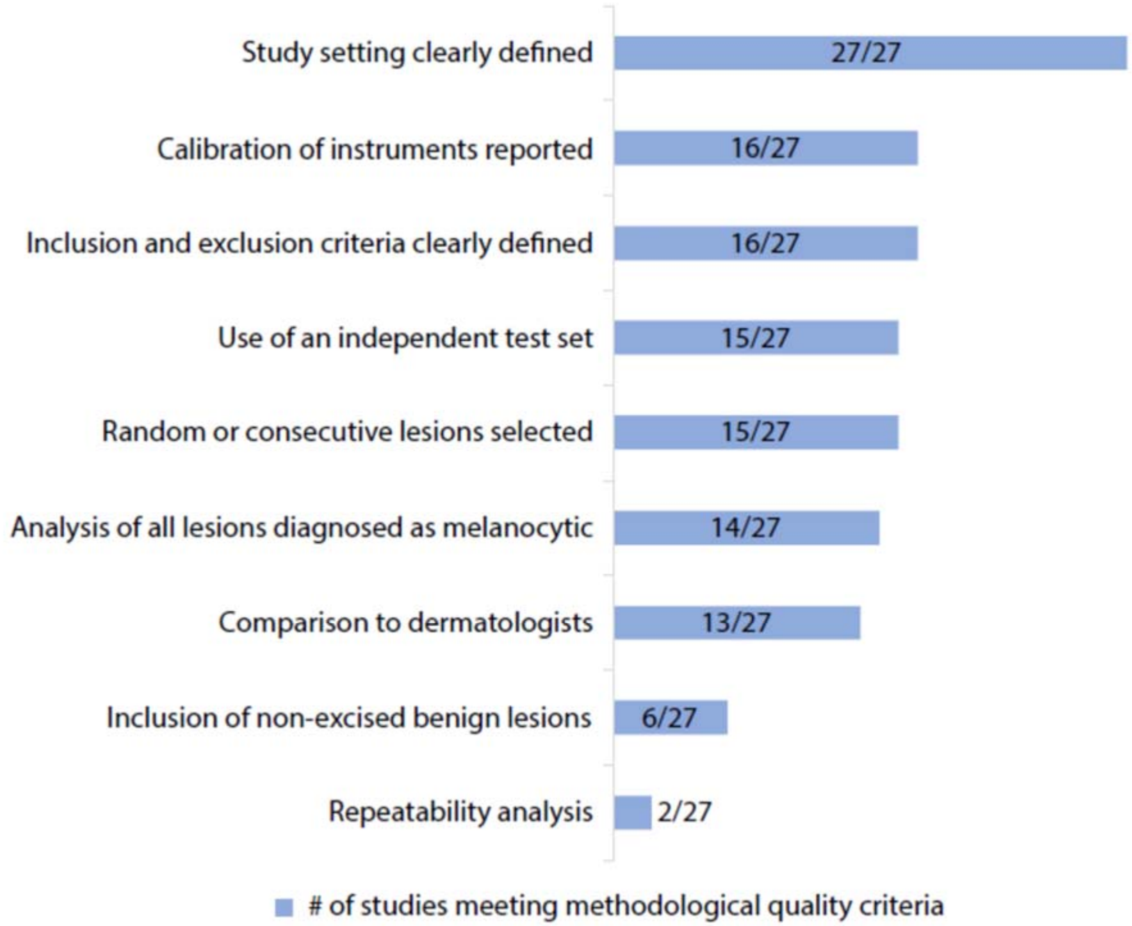
* Compared to Computer Vision

eFigure. Risk of Bias, Applicability Concerns, and Methodologic Quality

eFigure A, Summary of bias risk and applicability concern evaluations for studies included in the quantitative analysis (n = 70) using the QUADAS-2 tool.



eFigure B, Assessment of the methodologic quality of studies from the medical field (n = 27) using predefined criteria.



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