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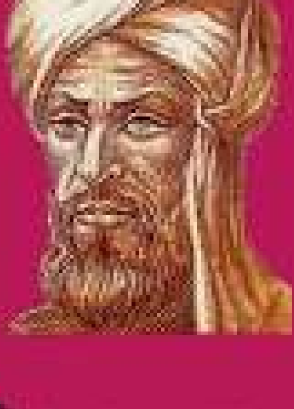

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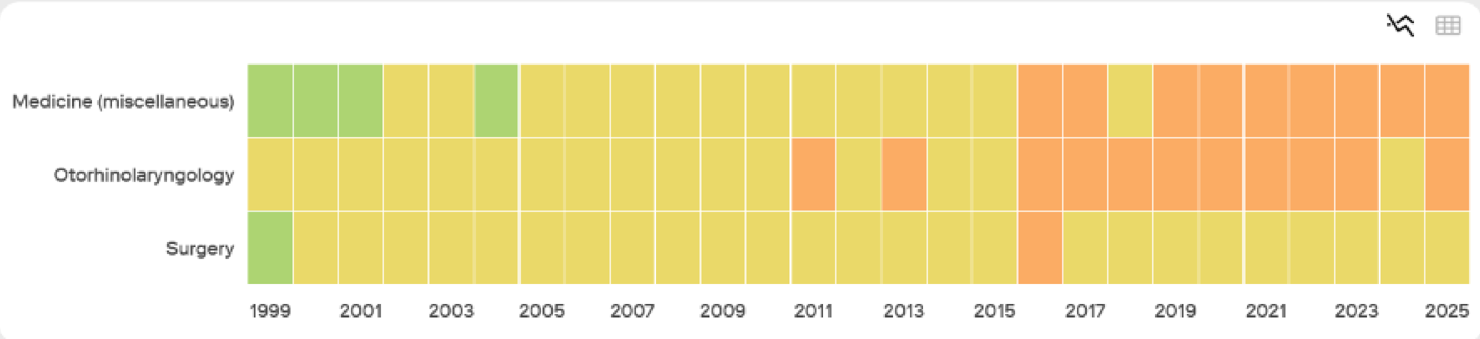

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SDC

The Role of Artificial Intelligence With Deep Convolutional Neural Network in Screening Melanoma: A Systematic Review and Meta-Analyses of Quasi-Experimental Diagnostic Studies

Stella Maureen Miracle, MD, Louis Rianto, MD,† Kelvin Kelvin, MD,† Kevin Tandarto, MD,* Felix Setiadi, MD,* Angela Angela, MD,‡ Thiara Maharani Brunner, MD,§ Hari Darmawan, MD,|| Henry Tanojo, MD,¶ Rosalyn Kupwiwat, MD,#** Inneke Jane Hidajat, MD,†† Rungsima Wanitphakdeedecha, MD, PhD,** and Kyu-Ho Yi, MD, PhD‡‡*

Introduction: Detecting melanoma as one of the most common skin cancer with using artificial intelligence (AI), such as deep convolutional neural network (DCNN) have the potency to increase the accuracy of the diagnosis. The aim of this study is to analyze the sensitivity, specificity, precision, and F1-score of DCNN in screening melanoma.

Methodology: The authors followed the PRISMA 2020 guidelines to retrieve literature in the following databases: PubMed, EBSCOhost, Emerald, Wiley, and ScienceDirect. The study's inclusion criteria were human quasi-experimental investigated DCNN in screening melanoma. The analysis was conducted using RevMan 5.4 and Quality Assessment of Diagnostic Accuracy Studies 2 (QUADAS-2) to ensure the quality of the studies.

Results: Fifty-six of 2386 articles published in 2003 to 2023 were included and 24 studies were statistically analyzed. Various type of DCNN was used [artificial neural network (n = 4); pigment network (n = 4); atypical pigment network (n = 1); ResNet (= 8); AlexNet (n = 3); visual geometry group (n = 7); inception (n = 4); custom DCNN (n = 4)]. The mean and median of total sample size in meta-analysis with melanoma subjects were (18,791; 2,157) with (573; 261), respectively. Overall, QUADAS-2 showed low risk of bias. Diagnostic performance was observed with pooled sensitivity (0.881), pooled specificity (0.897), and pooled AUC (0.894). The precision and F1-score were ranging from 58% to 98.83% and 0.45 to 0.98. The forest plot and summary receiver operating characteristics curve (SROC) of each multiple in multiple analysis showed satisfactory results.

Conclusions: DCNN showed significant result to screen melanoma in patients. It has the potential to help clinician in giving early screening.

Key Words: Artificial intelligence, melanoma, screening, skin cancer

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This study was conducted in compliance with the principles of the Declaration of Helsinki. Consent was received from the patients.
T.J.: conceptualization. T.J., J.K., S.Y.K., K.-H.Y.: writing—original draft preparation. J.K., S.Y.K., K.-H.Y.: writing—review and editing. T.J., J.K., K.-H.Y., J.W.: visualization. K.-H.Y.: supervision.
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Melanoma is a cancer that originates from melanocytes. In the USA, melanoma affects 22.1 of 100,000 people annually (Cancer statistics from the Centers for Disease Control and Prevention). Melanoma has a high mortality rate; it causes 75% of skin cancer deaths despite representing only 4% of all skin cancer cases. In 2019, 96,480 new cases of melanoma were reported in the USA, among those, 7230 resulted in death.[1–3] Although histopathologic examination remains the gold standard, it is invasive. Noninvasive methods, such as the use of dermoscope, aids in the early diagnosis of melanoma and other variants of melanocytic intraepidermal lesions.[3,4] The use of image analysis technology using computer programs, such as deep convolutional networks (DCNN) and other artificial intelligence (AI), has the potential to increase the survival rate of patients with melanoma.[5–7]

Artificial Intelligence (AI), particularly DCNN, has emerged as a groundbreaking technology in medical diagnostics.

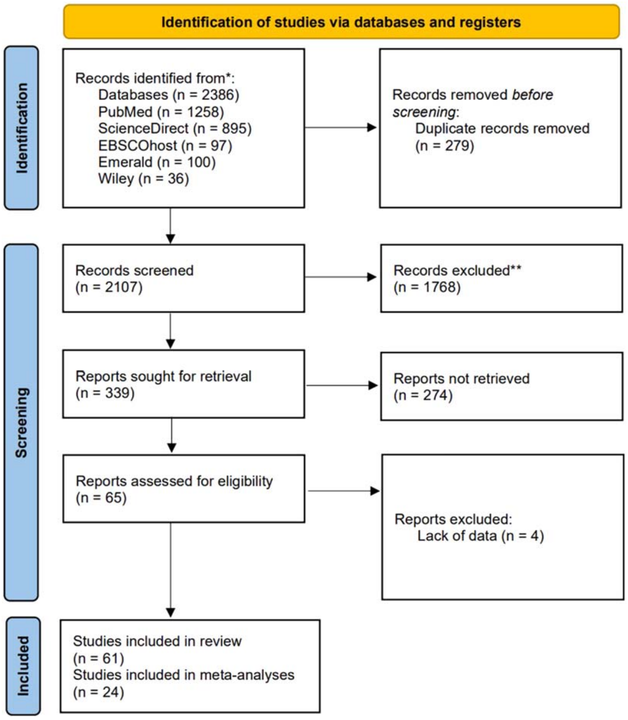


FIGURE 1. PRISMA flowchart 2020.

DCNNs are neural networks that are specially designed to analyze and process visual data. Unlike traditional image analysis techniques, DCNN utilizes multiple computational layers to extract complex features, making them highly effective for pattern recognition in medical imaging.[6] The unique architecture of DCNN enables the detection of intricate and subtle abnormalities, such as those present in dermoscopic images of melanoma.[7]

The combination of AI and DCNN technology has demonstrated remarkable potential in melanoma screening and diagnosis. Recent studies have demonstrated that DCNN-based models are comparable or even exceed the diagnostic accuracy of experienced dermatologists.[8] These models exhibit high sensitivity and specificity in identifying melanoma, effectively reducing false-negative rates and improving early detection.[9] Using automated image analysis, DCNN enhance clinical decision-making, allowing for faster and more objective assessments.[10]

Until now, no previously published meta-analysis on assessing the role of DCNN in diagnosing melanoma is available. The purpose of this paper is to determine the significance of DCNN in diagnosing melanoma. With faster and earlier diagnosis, it is hoped that therapy can be initiated quickly to reduce morbidity and mortality rates in melanoma patients.

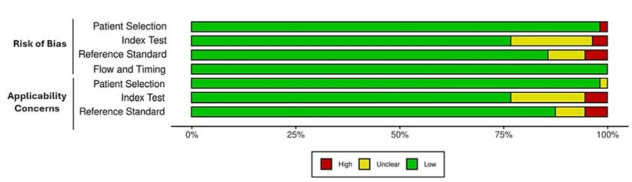


FIGURE 2. Traffic plot of QUADAS-2 risk of bias.

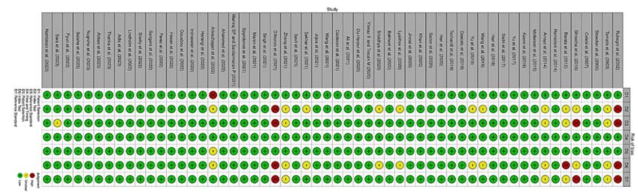


FIGURE 3. Summary plot of QUADAS-2 risk of bias.

METHODS

This study adhered to the Preferred Reporting Items guidelines for Systematic Reviews and Meta-analysis. Figure 1 shows the PRISMA 2020 checklist.

Literature Search

We conducted a comprehensive literature search to assess the potential of DCNN in screening melanoma from several databases: ProQuest, PubMed, EBSCOhost, SAGE, JSTOR, Emerald, Wiley, and ScienceDirect. The articles were retrieved with no time inception (until May 1, 2024). The search terms applied in PubMed are the following: (((((“skin”) AND ((“imaging”)) OR (“images”))) AND (“melanoma”)) OR ((“skin cancer”)) AND (“pigment*“)). A literature search was limited to those published in the English language and full-text. In addition, we manually searched additional possible studies for references.

Study Selection

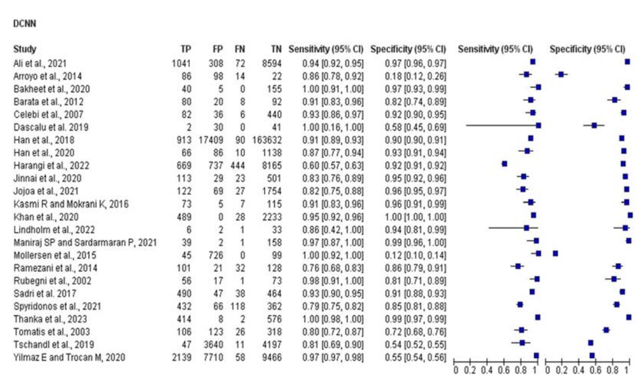
Literature search was limited to articles published in English and full-text was available. Studies were included if they met the inclusion criteria: (1) written in English, (2) full-text is available, (3) investigated the potency of DCNN in diagnosing melanoma. Studies were excluded if they were: (1) Reviews, letter to editor, case report; (2) repeat publications; (3) lack of data availability.

Data Extraction

The authors extracted further information independently about the research that has been included, using Rayyan. The extracted data were as follows: (1) the name of the first author and publication year; (2) country; (3) study design; (4) subjects (number of melanoma, number of nonmelanoma); (5) methods (sources, devices); (6) neural network family; (7) outcomes (sensitivity, specificity, accuracy, area under the curve, precision, and F1-scores).

Quality Assessment

Seven independent reviewers assessed the bias risk by applying the Quality Assessment of Diagnostic Accuracy Studies-2



DCNN

Study	TP	FP	FN	TN	Sensitivity (95% CI)	Specificity (95% CI)
Ali et al., 2021	1041	308	72	8594	0.94 [0.92, 0.95]	0.97 [0.96, 0.97]
Arroyo et al., 2014	86	98	14	22	0.86 [0.78, 0.92]	0.18 [0.12, 0.26]
Bakheet et al., 2020	40	5	0	155	1.00 [0.91, 1.00]	0.97 [0.93, 0.99]
Barata et al., 2012	80	20	8	92	0.91 [0.83, 0.96]	0.82 [0.74, 0.89]
Celebi et al., 2007	82	36	6	440	0.93 [0.86, 0.97]	0.92 [0.90, 0.95]
Dascalu et al. 2019	2	30	0	41	1.00 [0.16, 1.00]	0.58 [0.45, 0.69]
Han et al., 2018	913	17409	90	163632	0.91 [0.89, 0.93]	0.90 [0.90, 0.91]
Han et al., 2020	66	86	10	1138	0.87 [0.77, 0.94]	0.93 [0.91, 0.94]
Harangi et al., 2022	669	737	444	8165	0.60 [0.57, 0.63]	0.92 [0.91, 0.92]
Jinnai et al., 2020	113	29	23	501	0.83 [0.76, 0.89]	0.95 [0.92, 0.96]
Jojoa et al., 2021	122	69	27	1754	0.82 [0.75, 0.88]	0.96 [0.95, 0.97]
Kasmi R and Mokrani K, 2016	73	5	7	115	0.91 [0.83, 0.96]	0.96 [0.91, 0.99]
Khan et al., 2020	489	0	28	2233	0.95 [0.92, 0.96]	1.00 [1.00, 1.00]
Lindholm et al., 2022	6	2	1	33	0.86 [0.42, 1.00]	0.94 [0.81, 0.99]
Maniraj SP and Sardarmaran P, 2021	39	2	1	158	0.97 [0.87, 1.00]	0.99 [0.96, 1.00]
Mollersen et al., 2015	45	726	0	99	1.00 [0.92, 1.00]	0.12 [0.10, 0.14]
Ramezani et al., 2014	101	21	32	128	0.76 [0.68, 0.83]	0.86 [0.79, 0.91]
Rubegni et al., 2002	56	17	1	73	0.98 [0.91, 1.00]	0.81 [0.71, 0.89]
Sadri et al. 2017	490	47	38	464	0.93 [0.90, 0.95]	0.91 [0.88, 0.93]
Spyridonos et al., 2021	432	66	118	362	0.79 [0.75, 0.82]	0.85 [0.81, 0.88]
Thanka et al., 2023	414	8	2	576	1.00 [0.98, 1.00]	0.99 [0.97, 0.99]
Tomatis et al., 2003	106	123	26	318	0.80 [0.72, 0.87]	0.72 [0.68, 0.76]
Tschandl et al., 2019	47	3640	11	4197	0.81 [0.69, 0.90]	0.54 [0.52, 0.55]
Yilmaz E and Trocan M, 2020	2139	7710	58	9466	0.97 [0.97, 0.98]	0.55 [0.54, 0.56]

FIGURE 4. Forest plot of DCNN diagnostic performance.

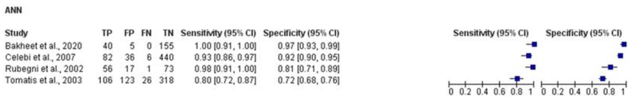


FIGURE 5. Forest plot of ANN diagnostic performance.

(QUADAS-2) risk of bias (RoB) tool. Any disagreements will be resolved through discussion by the corresponding author.

Statistical Analysis Outcome Measurement

The outcome of this review was to analyze and evaluate the accuracy, sensitivity, specificity, area under curve, precision, and F1-score. The included studies did not directly employ the use of human or animal subjects. Each study was conducted in compliance with the ethical standards specified therein. Statistical analysis was conducted using RevMan 5.4. Multiple analysis was conducted for Artificial Neural Network (ANN), ResNet, Visual Geometry Group Network (VGG), Pigment Network, GoogleNet, and custom.

RESULTS

A total of 2386 articles were obtained from literature search of databases. After the removal of duplicates and screening, 61 articles were included in the systematic review and 24 articles were included in the meta-analysis. The PRISMA 2020 flowchart can be seen in Figure 1. The risk of bias of included studies was then assessed using the QUADAS-2 for diagnostic studies. It was found that the majority of studies had a low risk of bias (Figs. 2 and 3).

From the systematic review of 61 studies (Supplement Table 1, Supplemental Digital Content 1, http://links.lww.com/SCS/H876), it was found that the sensitivity ranged from 38% to 100% with a mean of 84.95% and a pooled (0.881). Specificity ranged from 53.5% to 100% with a mean of 86.89% and pooled (0.897). Accuracy ranged from 74% to 99.1% with a mean of 89.93%, and pooled AUC (0.894). Meanwhile, precision and F1-score ranged from 58% to 98.83% and 45% to 98%, respectively, with a mean precision of 80.49% and a mean F1-score of 78.18%.

The lowest sensitivity (38%) was obtained in the study by Sevil et al,[11] whereas the highest (100%) was in research observed in the study by Bakheet et al[12] Meanwhile, the lowest specificity (53.5%) was obtained in the research by Tschandl et al[13] and the highest (100%) in the research conducted by Khan et al.[10] In terms of accuracy, the lowest value (74%) was obtained in the research by Tomatis et al[14] and the highest value (99.1%) was obtained in the study by Roshni Thanka et al[15] The highest precision value and F1-score (each 98.83%) were obtained in the research of Balaha et al.[8] Through statistical analysis of the 24 studies selected for meta-analysis, sensitivity was shown to range from 0.76 to 1.00, with the majority >0.85. Specificity varied more widely, from 0.12 to 1.00. The DCNN model showed high sensitivity, but some studies have noted difficulty in correctly identifying nonmelanoma (true negative) cases as seen in Figure 4. In the multiple analysis of artificial neural network (ANN) ($n=4$), sensitivity ranged from 0.72 to 1.00. Specificity ranged from 0.72 to 0.97. ANN showed high

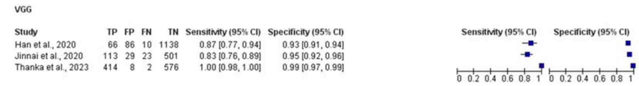


FIGURE 7. Forest plot of VGG diagnostic performance.

sensitivity and relatively balanced ability to correctly classify nonmelanoma cases, compared with DCNN, as seen in Figure 5. In the ResNet ($n=4$) multiple analysis, sensitivity ranged from 0.79 to 0.91. Specificity ranged from 0.85 to 0.90. The ResNet model performs well in terms of sensitivity, with high specificity as seen in Figure 6. In the visual geometry group network (VGG; $n=3$) multiple, sensitivity ranged from 0.87 to 1.00. Specificity ranged from 0.93 to 0.99. VGG showed high sensitivity, with consistent specificity as seen in Figure 7. In the multiple analysis of the pigment network ($n=4$), sensitivity ranged from 0.86 to 1.00. Specificity ranged from 0.12 to 0.96. Pigment Network showed high sensitivity, but lower specificity compared with other models as seen in Figure 8. In the GoogleNet multiple, sensitivity ranged from 0.93 to 1.00. Specificity ranged from 0.55 to 1.00. GoogleNet showed high sensitivity, with lower specificity compared with other models as seen in Figure 9. In the custom multiple, sensitivity showed a high range, from 0.86 to 0.94. Specificity ranged between 0.91 and 0.94. Custom networks showed high sensitivity and specificity as seen in Figure 10.

The majority of models (especially DCNN, ANN, and Custom) were clustered in the upper left portion of the plot, indicating high sensitivity (>0.80) and high specificity (around 0.80–1.00). These models were significantly effective in screening melanoma while maintaining accuracy in identifying nonmelanoma cases. By plotting the data into the summary receiver operating characteristics (SROC) curve, it was found that all 24 studies were located above the curve. Models using DCNN, ANN, and custom were found to be located in the upper left portion of the plot (Fig. 11).

Sensitivity ranging from 0.71 to 1.00. Specificity Ranging from 0.12 to 1.00. DCNN with dermoscopy showed high sensitivity, with various specificity. Another multiple analysis was carried out on the sensitivity and specificity of combining DCNN with dermoscopy ($n=22$). Sensitivity was found to range from 0.71 to 1.00, specificity ranged from 0.12 to 1.00. Combination of DCNN with dermoscopy shows a high sensitivity, but heterogenous results of specificity (Fig. 12).

The majority of data points were clustered in the upper left quadrant of the plot, with high sensitivity (0.80–1.00) and high specificity (0.70–1.00). DCNN with dermoscopy were highly sensitive in screening true melanoma cases (low false negatives). Specificity was also generally high, but with some variability across the data points. By plotting the data from the combination of DCNN and dermoscopy into the summary receiver operating characteristics (SROC) curve, it was found that all 22 studies were located above the curve (Fig. 13).

As indicated in Supplement Tables 2 and 3, Supplemental Digital Content 1, http://links.lww.com/SCS/H876, the majority of the included studies' GRADE Quality of Evidence Assessments indicated moderate to high evidence quality. Small sample sizes and variations in study designs are the main

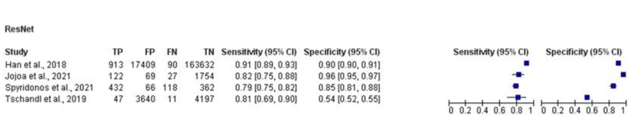


FIGURE 6. Forest plot of ResNet diagnostic performance.

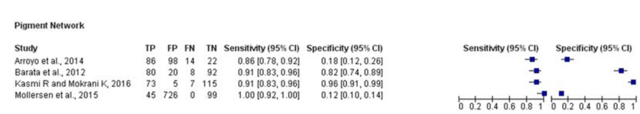


FIGURE 8. Forest plot of PN diagnostic performance.

GoogleNet

Study	TP	FP	FN	TN	Sensitivity (95% CI)	Specificity (95% CI)
Dascalu et al. 2019	2	30	0	41	1.00 [0.16, 1.00]	0.58 [0.45, 0.69]
Khan et al., 2020	489	0	28	2233	0.95 [0.92, 0.96]	1.00 [1.00, 1.00]
Yilmaz E and Trocan M, 2020	2139	7710	58	9466	0.97 [0.97, 0.98]	0.55 [0.54, 0.56]

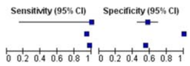


FIGURE 9. Forest plot of GoogleNet diagnostic performance.

drawbacks. However, despite minor imprecision caused by wide CI, our study provides valuable insight into melanoma screening in the clinical setting.

DISCUSSION

This systematic review and meta-analysis highlighted the direct comparison of DCNN in diagnosing and screening melanoma between available studies, from methods to efficacy. To enhance the quality of the systematic review, we conducted a statistical analysis to draw a conclusion.

The overall outcome of using DCNN in machine learning was satisfactory in distinguishing melanoma in patients. Our results found pooled sensitivity (0.881), pooled specificity (0.897), and pooled AUC (0.894). The precision and F1-score ranged from 58% to 98.83% and 0.45 to 0.98, respectively. The findings were in line with the research conducted by Patel and colleagues, which aimed to assess the current usage of AI-based methods alongside noninvasive diagnostic imaging techniques for melanoma detection. AI algorithms consistently demonstrated robust performance, with an average ROC (receiver operating characteristic) exceeding 80% in identifying melanoma. In analyses using dermoscopic images, the average sensitivity and specificity of the algorithms were ~83.01% and 85.58%, respectively.[9]

The DCNN represents a specialized category of artificial neural networks (ANN) that utilize convolution instead of general matrix multiplication in at least one layer. Unlike simple neural networks with limited hidden layers, CNNs are composed of numerous layers, enabling them to effectively capture complex and nonlinear functions. CNN architecture typically features various types of layers, such as convolutional, pooling, and fully connected layers, incorporating regularization techniques. To comprehend intricate features and functions necessary for representing high-level abstractions in tasks like vision and language processing, CNNs require deep architectures. These deep architectures, including CNNs, are characterized by a large number of neurons and multiple layers facilitating the computation of nonlinear transformations.[6]

Despite the promising results of DCNN, particularly when combined with several devices, our study has a number of drawbacks. The absence of a standardization procedure among protocols could result in false positives and false negatives. Varied devices between studies and small sample sizes may possibly have an impact on the study's findings. Randomized controlled trials are needed to create a standardized methodology for the diagnostic protocols for DCNN in screening melanoma.

Although DCNN models have demonstrated diagnostic performance comparable to, or in some cases surpassing, that of experienced dermatologists, we believe these systems are best positioned as augmented intelligence tools, rather than replacements for clinicians. Their role is to support and enhance

Custom

Study	TP	FP	FN	TN	Sensitivity (95% CI)	Specificity (95% CI)
Ali et al., 2021	1041	308	72	8594	0.94 [0.92, 0.95]	0.97 [0.96, 0.97]
Lindholm et al., 2022	6	2	1	33	0.86 [0.42, 1.00]	0.94 [0.81, 0.99]

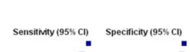


FIGURE 10. Forest plot of custom DCNN diagnostic performance.

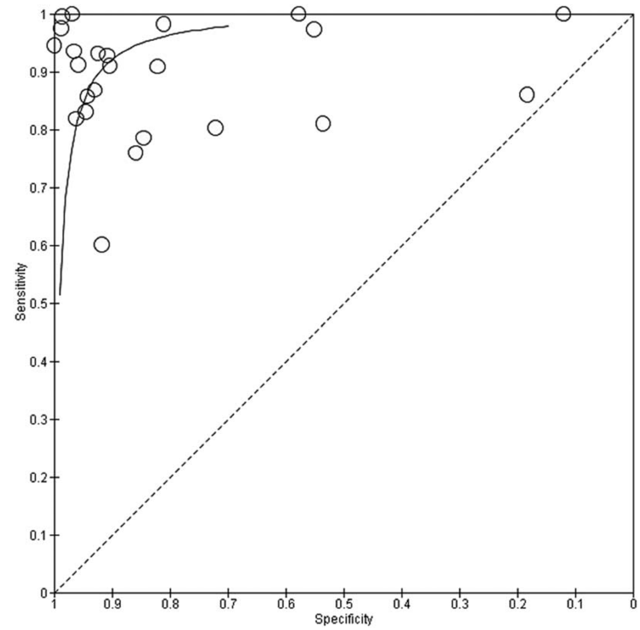


FIGURE 11. Summary receiver operating characteristic (SROC) curve of the included studies.

decision-making by providing rapid, objective assessments of dermoscopic images, especially in settings with limited access to dermatology specialists. Ultimately, clinical judgment remains irreplaceable, as patient history, physical examination, and holistic evaluation are essential components of diagnosis and management. Therefore, DCNN should be viewed as assistive technology that complements—not supplants—human expertise.[15–32]

The medico-legal implications of AI-assisted diagnosis remain an evolving area. Current guidelines suggest that clinicians remain responsible for final diagnostic decisions, even when using AI tools. Regulatory bodies, such as the FDA and EMA, have begun issuing frameworks for Software as a Medical Device (SaMD), emphasizing transparency, validation, and traceability. In the event of a misdiagnosis, liability typically depends on how the AI system was used (eg, as a decision aid versus autonomous decision-maker), whether it met regulatory standards, and whether the clinician adhered to best practices. Further legal clarity is needed, but ethical deployment requires proper validation, informed consent, and clinician oversight.[32–48]

The implementation costs of DCNN technology vary depending on the system's complexity, integration with existing electronic health records, and whether it is cloud-based or locally hosted. Open-source models (eg, those trained using public

Study	TP	FP	FN	TN	Sensitivity (95% CI)	Specificity (95% CI)
Ali et al., 2021	1041	308	72	8594	0.94 [0.92, 0.95]	0.97 [0.96, 0.97]
Arroyo et al., 2014	86	98	14	22	0.86 [0.78, 0.92]	0.18 [0.12, 0.26]
Bakheet et al., 2020	40	5	0	155	1.00 [0.91, 1.00]	0.97 [0.93, 0.99]
Barata et al., 2012	80	20	8	92	0.91 [0.83, 0.96]	0.82 [0.74, 0.89]
Celebi et al., 2007	82	36	6	440	0.93 [0.86, 0.97]	0.92 [0.90, 0.95]
Dascalu et al. 2019	2	30	0	41	1.00 [0.16, 1.00]	0.58 [0.45, 0.69]
Han et al., 2018	913	17409	90	163632	0.91 [0.89, 0.93]	0.90 [0.90, 0.91]
Han et al., 2020	66	86	10	1138	0.87 [0.77, 0.94]	0.93 [0.91, 0.94]
Harangi et al., 2022	669	737	444	8165	0.60 [0.57, 0.63]	0.92 [0.91, 0.92]
Jinnai et al., 2020	113	29	23	501	0.83 [0.76, 0.89]	0.95 [0.92, 0.96]
Jojoa et al., 2021	122	69	27	1754	0.82 [0.75, 0.88]	0.96 [0.95, 0.97]
Kasmi R and Mokrani K, 2016	73	5	7	115	0.91 [0.83, 0.96]	0.96 [0.91, 0.99]
Khan et al., 2020	489	0	28	2233	0.95 [0.92, 0.96]	1.00 [1.00, 1.00]
Maniraj SP and Sardarmaran P, 2021	39	2	1	158	0.97 [0.87, 1.00]	0.99 [0.96, 1.00]
Mollersen et al., 2015	45	726	0	99	1.00 [0.92, 1.00]	0.12 [0.10, 0.14]
Ramezani et al., 2014	101	21	32	128	0.76 [0.68, 0.83]	0.86 [0.79, 0.91]
Rubegni et al., 2002	56	17	1	73	0.98 [0.91, 1.00]	0.81 [0.71, 0.89]
Sadri et al. 2017	490	47	38	464	0.93 [0.90, 0.95]	0.91 [0.88, 0.93]
Spyridonos et al., 2021	432	66	118	362	0.79 [0.75, 0.82]	0.85 [0.81, 0.88]
Thanka et al., 2023	414	8	2	576	1.00 [0.98, 1.00]	0.99 [0.97, 0.99]
Tschandl et al., 2019	47	3640	11	4197	0.81 [0.69, 0.90]	0.54 [0.52, 0.55]
Yilmaz E and Trocan M, 2020	2139	7710	58	9466	0.97 [0.97, 0.98]	0.55 [0.54, 0.56]

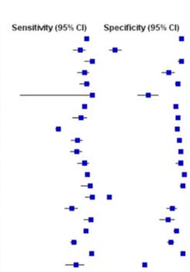


FIGURE 12. Forest plot of DCNN with dermoscopy.

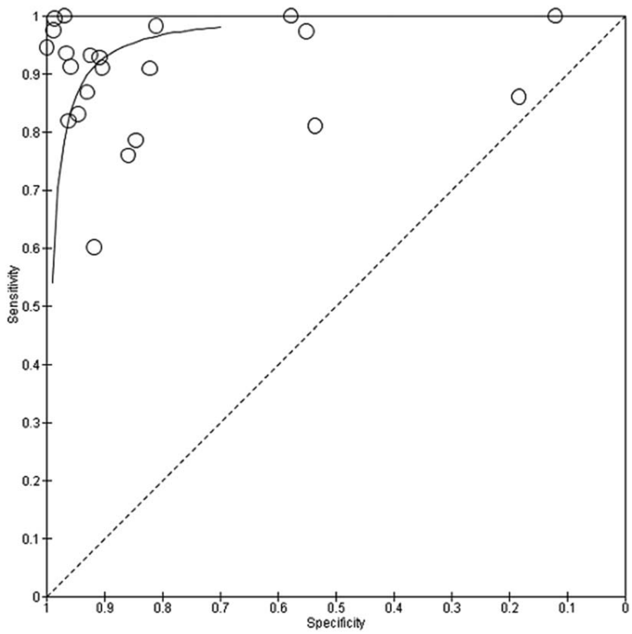


FIGURE 13. Summary receiver operating characteristic (SROC) curve of DCNN with dermoscopy.

data sets like ISIC) offer a low-cost entry point but still require infrastructure and expertise for deployment. Commercial solutions can involve licensing fees, typically ranging from a few thousand to tens of thousands of dollars annually, depending on scale. In terms of time, once deployed, DCNN systems provide near-instantaneous image analysis, significantly reducing the time burden on clinicians. Cost-benefit analyses suggest that, when applied appropriately, AI systems may reduce unnecessary biopsies, improve triage, and optimize dermatology referrals, thereby offering long-term savings.[48–62]

CONCLUSION

From our study, we can conclude that applying DCNN in machine learning was satisfactory in screening melanoma in patients. DCNN, with and without a dermoscope, has the potential to diagnose skin cancer. Thus, DCCN has the potential to aid clinicians in early screening and diagnosing, allowing patients to quickly initiate treatment. These studies have become a big stone in the development of diagnosis techniques. As for now, the usage of AI is limited to focusing on the appearance of skin lesions. Therefore, clinicians still need to approach patients holistically to obtain the full diagnosis.

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