Artificial Intelligence in Patch Testing: A Comprehensive Review of Current Applications and Future Prospects in Dermatology

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Table of Contents

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Abstract

Background: The integration of artificial intelligence (AI) into patch testing for allergic contact dermatitis (ACD) holds the potential to standardize diagnoses, reduce inter-observer variability, and improve overall diagnostic accuracy. However, the challenges faced by the field and the limitations hindering clinical implementation have not been thoroughly explored.

Objective: This narrative review aims to examine the current applications of AI in patch testing, identify challenges, and propose future directions for their use in dermatology.

Methods: PubMed was searched in August 2024 to identify studies involving human participants undergoing patch testing with AI or ML interventions. Exclusion criteria were non-English articles and non-original research. Data were synthesized to assess study design, performance, and potential for clinical application.

Results: Ten out of 94 reviewed articles met the inclusion criteria. The majority utilized convolutional neural networks (CNNs) for image analysis, with accuracy rates ranging from 90.1% to 99.5%. Other AI models, such as Gradient Boosting and Random Forest, were used for risk prediction and biomarker discovery. Key limitations included limited sample sizes, variability in image capture protocols, and lack of standardized reporting on skin types.

Conclusions: AI has significant potential to enhance diagnostic accuracy and standardize patch test interpretation with the potential to help expand access to patch testing. However, standardized imaging protocols, larger and more diverse datasets, and improved regulatory frameworks are necessary to realize the full potential of AI in patch testing.

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Keywords: Artificial Intelligence; Machine Learning; Patch Testing; Allergic Contact Dermatitis

Introduction:

Allergic contact dermatitis (ACD) is a common inflammatory skin condition affecting approximately 20% of the population, with significant impacts on patients' quality of life and productivity [1,2]. Traditional patch testing methods, while effective for diagnosing ACD, can be time-consuming and

subject to inter-observer variability [3,4]. As technology continues to advance, the integration of artificial intelligence (AI) offers the possibility of standardizing interpretations, reducing human error, and potentially improving the overall diagnostic process in patch testing [5].

AI, broadly defined as the ability of computer systems to mimic human cognitive functions, encompasses various computational subfields including machine learning (ML). Furthermore, deep learning (DL), a subset of ML, utilizes algorithms modeled after human neurons to detect complex patterns and relationships in data [6]. These AI technologies have shown promising applications in dermatology, ranging from identifying skin malignancies to classifying inflammatory skin conditions and analyzing clinical notes. The visual nature of dermatology, combined with the increasing volume of clinical photographs, dermoscopy images, abundance of psychometric data from wearable devices, and electronic health records, makes it particularly well-suited for AI-augmented patient care [6,7,8].

The use of AI in patch testing is particularly intriguing due to the complex nature of interpreting patch test results. Several factors, such as weak positive reactions, irritant reactions, and the timing of readings can all influence the accuracy of diagnoses [9,10,11,12]. With the integration of AI algorithms, these challenges could potentially be mitigated, leading to more accurate and consistent interpretations of patch test results. However, the implementation of AI into clinical practice is not without its own challenges. Issues such as algorithm bias, clinical accuracy, data privacy, and the need for large, diverse datasets for training must be carefully considered [13,14]. Additionally, the integration of these technologies into the existing clinical workflow and their acceptance by both physicians and patients are important factors to consider.

This narrative review aims to explore the current landscape of AI applications in patch testing for

ACD. We will examine the types of algorithms that are currently being researched, their performance, the challenges faced, and potential future directions for this rapidly evolving field. By synthesizing the available literature, we hope to provide a comprehensive overview of the state of AI in patch testing and how AI can be leveraged to improve patch testing practices and diagnostic accuracy of ACD in the future.

Methods:

Search Strategy:

A comprehensive literature search was performed in August 2024 using the PubMed database. The search was conducted without date restrictions to capture the full scope of research in this emerging field. This broad approach ensured that all relevant studies, regardless of publication date, were included, providing a more thorough evaluation of AI applications in patch testing and the observance of any trends over time. Literature searches were conducted using combinations of keywords, such as "artificial intelligence," "machine learning," "patch testing," and "contact dermatitis" or “skin" (see *Supplementary Table S1* for full search term list). These terms were chosen to ensure a wide net was cast, incorporating both general AI terms and specific patch testing and dermatology-related concepts.

Supplementary Table S1: Search Terms Used for This Review

Category	Search Terms
Machine learning	("Machine Learning"[Mesh] OR "Artificial Intelligence"[Mesh] OR "Deep Learning"[Mesh] OR "Supervised Machine Learning"[Mesh] OR "Support Vector Machine"[Mesh] OR "Unsupervised Machine Learning"[Mesh] OR "Computer Heuristics"[Mesh] OR "Natural Language Processing"[Mesh] OR "Neural Networks, Computer"[Mesh] OR "Expert Systems"[Mesh] OR "Fuzzy Logic"[Mesh] OR "Machine Learning" OR "Artificial Intelligence" OR "Deep Learning" OR "Augmented Intelligence" OR "Large Language Models" OR "Foundation Models" OR "Neural Networks" OR "Convolutional Neural Networks" OR "Supervised Learning" OR "Unsupervised Learning" OR "Natural Language Processing" OR "Image Analysis" OR "Pattern Recognition" OR "Data Mining" OR "Decision

	Support Systems" OR "Machine Intelligence" OR "Cognitive Computing" OR "Automated Diagnosis" OR "Predictive Modeling" OR "Computer Vision" OR "Image Recognition" OR "Algorithmic Diagnosis" OR "Ensemble Learning" OR "Health Informatics" OR "Diagnostic Decision Support" OR "Expert Systems" OR "Computer-Aided Diagnosis" OR "reinforcement learning" OR "Generative Adversarial Network")
Patch Test	("Patch Tests"[Mesh] OR "patch test" OR "patch testing" OR "patch tests" OR "Patch Test Allergens" OR “Drug Patch Test” OR epicutaneous test OR Contact Sensitization Testing)
Skin	(skin OR epicutaneous OR cutaneous OR epidermis OR “skin barrier” OR skin inflammation OR skin sensitization)
Contact Dermatitis	("Dermatitis, Contact"[Mesh] OR "contact dermatitis" OR "Dermatitis, Allergic Contact"[Mesh] OR Allergic Eczematous Dermatitis OR Allergic Contact Dermatitis OR "Dermatitis, Photoallergic"[Mesh] OR Photocontact Dermatitis OR Photosensitive Dermatitis OR photoallergic OR photoallergy OR "Allergic Dermatitis" OR "Contact Allergy" OR "Contact Sensitivity" OR "Contact Hypersensitivity" OR Dermatitis Allergic Occupational OR "Dermatitis, Occupational"[Mesh] OR Industrial Dermatosis OR "occupational dermatitis" OR dermatitis)))

Inclusion and Exclusion Criteria:

Criteria for inclusion and exclusion were defined prior to screening to reduce potential biases. Studies were included if they met the following criteria: the population consisted of human patient populations undergoing patch testing; the study design involved AI (which includes ML and DL); and outcomes reported on the performance of these algorithms. All publication types, including journal articles, conference abstracts, and preprints, were considered. Studies were excluded if they were not written in English or if they were not original research, such as review papers or perspectives.

Study Selection Process and Data Extraction:

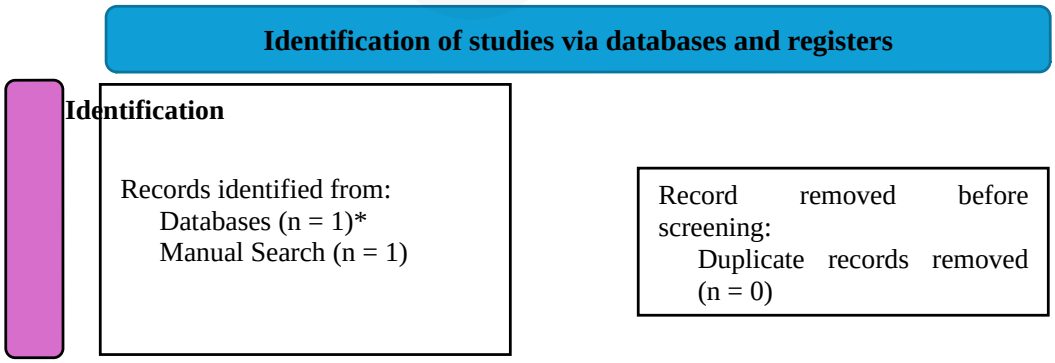
The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) approach was selected to ensure transparency and replicability in the selection process, providing a clear pathway from initial search to final inclusion [15,16]. Each article was independently reviewed by two reviewers, and in cases of disagreement, a third reviewer assessed the article to determine its inclusion in the study to enhance the reliability and accuracy of inclusion decisions and reduce the

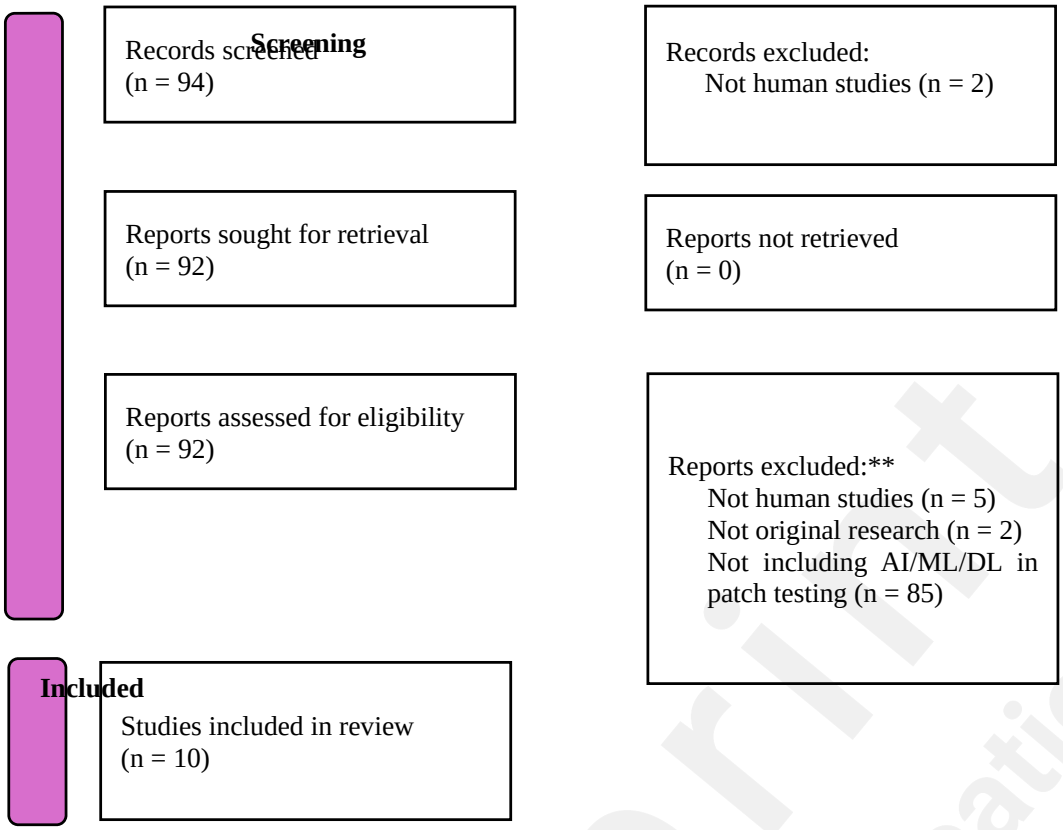
risk of individual reviewer bias. From the included studies, the following data elements were then extracted: study design; sample size; skin types included; length of study for each participant; location of study; materials used (such as types of patches); type of AI algorithm and its performance in the study; limitations and challenges of the study; and future directions. The findings were then synthesized to highlight trends, gaps, and potential areas for future research in the application of AI in patch testing. This synthesis serves as a foundation for guiding future research efforts, with the goal of synthesizing both technical and clinical factors of the clinical patch testing procedure, analysis, data capturing, image capturing and storage, AI algorithms, and diagnostic accuracy comprehensively, contributing to the current gaps in the current practice of AI integration within dermatological patch testing diagnostics.

Results:

A total of 94 records were ultimately screened and evaluated for eligibility, as shown in the PRISMA flow diagram (*Figure 1*) [15]. Of the 94 articles, our literature review identified 10 relevant studies which employed various AI techniques in the context of patch testing and skin sensitization prediction as shown in *Table 1*. These studies encompassed a wide range of approaches, from image analysis of patch test results to molecular profiling and risk prediction models.

Figure 1: PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 flow diagram for the identification of studies [15]





*Databases used in this narrative review: PubMed

**Reports excluded: Does not meet inclusion criteria: 1) *Population*: All patient populations (humans) undergoing patch testing 2) *Interventions*: Studies designs and performance of artificial intelligence (AI) / machine learning (ML) / deep learning (DL) algorithms in patch testing 3) *Outcomes*: Non-English and non-original research (e.g.; review papers, perspectives) were excluded for the purposes of this narrative review.

Table 1:

uthor, ear	Study Objective	Type of AI Algorithm Used	Location	Skin Types Included; Demographics (n, %)	Materials Used	Dermatologist Involvement (Yes/No)	Training Data Sample Size	Test/ Validation Data Sample Size	Accuracy/ Performance
yritsi et ., 2024	To investigate the contact allergy patterns	Multiple Correspondence Analysis (MCA), Categorical Principal Components Analysis (CATPCA)	Greece	N/A	4 allergens	Yes	800 patients	N/A	N/A
avishank et al., 024	To evaluate the use of convolutional neural networks to determine presence of patch test reactions	Convolutional Neural Network (CNN)	United States	Fitzpatrick Skin Types I-II: 110 (88%), III-V: 15 (12%) Caucasian: 100 (80%), Black: 4 (3.2%), Asian: 6	N/A	Yes	125 patients. 13,622 images.	2,725 images	AUC: 0.940, Accuracy: 90.1%, Sensitivity: 86.0%, Specificity: 90.2%

				(4.8%), Unknown: 15 (12%)					
all et al., 024	To develop a deep learning algorithm for the analysis of patch testing	CNN	United States	White: 165 (82.1%), Black or African American: 20 (10.0%), Asian: 5 (2.5%), Other or Unknown: 11 (5.5%)	80 allergens (Mayo Clinic standard series) were used for all patients; specific series/ panels varied by patient.	Yes	201 patients. 2,810 image tiles.	507 images	AUC: 0.885, Accuracy: 90.9%, Sensitivity: 70.1%, Specificity: 91.7%, F1 Score: 37.1
yritsi et ., 2023	To investigate the patterns of contact sensitization	Multiple Correspondence Analysis (MCA)	Greece	Greek Caucasian: 240 (100%)	3 allergens	Yes	240 patients	N/A	N/A
ezakis et ., 2023	To investigate the feasibility of using a deep learning classifier for automating the identification of allergens causing ACD	CNN	Greece	N/A	30 allergens	Yes	200 patients. 1,190 images	Validation set: 357 images	Pre-processing scheme comparison: F1 Score: 0.83, Accuracy: 90%, Specificity: 95%, Recall: 79%, Precision: 87%
efevre et ., 2021	To characterize the molecular signatures of chemical-induced skin inflammation through comprehensive transcriptomic analysis	Boruta, Random Forest (RF)	France, Belgium	N/A	6 allergens, 3 irritants	Yes	47 patients	N/A	Accuracy: 90-100%
han et ., 2021	To develop a machine learning approach for accurate classification of patch-test photographs.	CNN	United States	Fitzpatrick Skin Types I: 2 (2.6%), II: 28 (36.4%), III: 29 (37.7%), IV: 14 (18.2%), V: 4 (5.2%)	80 allergens (American Contact Dermatitis Society (ACDS) Core Screening Allergen Series)	Yes	77 patients. 3,695 images.	CNN training set: 1,118 images. Validation set: 373 images. Test set: 2,204 images.	AUC: 0.915, Accuracy: 99.5%, F1 Score: 0.89
unningha et al., 021	To compare the predictive accuracy of logistic regression with more sophisticated machine learning approaches such as gradient boosting in predicting patch testing results	Gradient Boosting, RF, AdaBoost, Logistic Regression (LR)	United Kingdom	N/A	36 allergens	Yes	42,434 patients	Test set: 10,609 patients	Gradient Boosting: AUC mean 0.69 (SD 0.06), RF: AUC mean 0.60 (SD 0.052). AdaBoost: AUC mean 0.58 (SD 0.048). LR: AUC mean 0.65 (SD 0.068).
ortino et ., 2020	To identify and validate biomarkers to distinguish allergic and irritant contact dermatitis in human skin.	GARBO (novel Genetic Algorithm with RF-based classifier), RF, CIBERSORT, INfORM (Inference of Regulatory Modules)	Finland	N/A	4 allergens	Yes	85 patients. 89 patch test biopsies.	Validation set: 31 patch test biopsies	GARBO Accuracy: 86%-94%, F1 Score: 94% for Allergic Contact Dermatitis (ACD), 92% for Irritant Contact

									Dermatitis (ICD)
dler et l., 2017	To identify if certain pairs of positive reactions to allergens may be associated with polysensitization.	RF, LR	Germany, Switzerland, Austria	N/A	24 allergens	No	105,325 patients.	Tuning set: 35,294. Validation set: 70,031.	RF: N/A. LR: AUC > 0.90.

Characteristics of Included Studies:

Geographically, the studies were conducted across various countries and continents, with the United States (3 studies) and Greece (3 studies) being the most represented. The remaining studies were distributed across other European countries, including the United Kingdom, Finland, and a multi-country study spanning Germany, Switzerland, and Austria. Sample sizes also varied considerably between the studies, ranging from 47 patients in the molecular signature study by Lefevre et al. [17] to 105,325 patients in the large-scale analysis by Adler et al [18]. The materials used for patch testing varied, with many employing standard European baseline series allergens. However, some studies, such as Lefevre et al. [17] and Fortino et al. [19], used specific sets of allergens and irritants for their molecular profiling approaches. Regarding skin types, only three out of the 10 studies reported on the distribution of skin tones in their datasets. Hall et al. [20] reported that 82% of their sample was White and had lighter Fitzpatrick skin types (typically I-III). Chan et al. [21] included Fitzpatrick skin types I-V, with the majority falling into Fitzpatrick II-III. Ravishankar et al. [22] showed a significant imbalance, with 88% of images representing lighter skin tones (Fitzpatrick I-II).

AI and ML Techniques Used:

Overall, Convolutional Neural Networks (CNNs) were the most commonly used algorithms for image analysis of patch test reactions, appearing in four of the ten studies (Hall et al. [20], Chan et al. [21], Ravishankar et al. [22], and Vezakis et al. [23]). These CNN-based models demonstrated high

accuracy in identifying and classifying patch test reactions. The study by Hall et al. [20] reported an accuracy of 90.9% with an AUC of 0.885, while Chan et al. [21] achieved an even higher accuracy of 99.5% with an AUC of 0.915. Similarly, Ravishankar et al. [22] and Vezakis et al. [22] reported accuracies of 90.1% and 90%, respectively, further supporting the potential of CNNs use in patch test interpretation. Other approaches, such as Random Forest, Gradient Boosting, and Logistic Regression, were employed in studies focusing on risk prediction and biomarker discovery (Cunningham et al. [24], Lefevre et al. [17], Fortino et al. [19], and Adler et al. [18]). Notably, the study by Cunningham et al. [24] compared multiple algorithms and found that Gradient Boosting outperformed other methods, including Logistic Regression, with an AUC of 0.69 for predicting cutaneous allergy risk. Two studies (Kyritsi et al., 2023 [25] and 2024 [26]) utilized Multiple Correspondence Analysis to investigate patterns and relationships in patch test data, particularly in the context of occupational dermatitis and population-specific sensitization profiles. While these studies did not provide specific accuracy metrics, they demonstrated the utility of AI techniques in uncovering complex associations within patch test data.

Discussion:

This review of 10 studies exploring the application of AI techniques in patch testing reveals promising advancements along with numerous challenges and limitations. The diverse range of approaches, from image analysis to molecular profiling and risk prediction, demonstrates the versatility of AI in addressing various aspects of contact dermatitis diagnosis and patch testing in general.

The high accuracy achieved by CNN-based models in analyzing patch test images is particularly significant. With accuracies ranging from 90.1% to 99.5%, these models show great potential for automating and standardizing patch test interpretation, as some studies have shown inter-rater variability in diagnosing patch test reactions [4]. This could lead to more consistent diagnoses across

different clinical settings and potentially reduce the workload for dermatologists and help expand access to patch testing. One key barrier is the need for standardized imaging protocols. The variability in the quality of images, as well as the inconsistency in how and when these images are captured, introduces a significant source of error in AI models. Standardized, high-quality image capture and storage protocols are essential for ensuring that AI systems can be effectively trained and applied across different clinical settings.

Moreover, our review underscores the necessity for large, diverse, and representative image databases to train AI models. The development of these datasets will require multi-institutional collaboration with diverse skin types. The creation of a global patch testing image repository would not only improve AI model performance, but also accelerate the discovery of new dermatological insights, enable the continuous refinement of diagnostic algorithms, and increase diagnosis assistance for complex cases, especially in lower resource settings.

The application of other techniques such as Random Forest, Gradient Boosting, and Logistic Regression in risk prediction and biomarker discovery is also promising. The study by Cunningham et al. [24], which found Gradient Boosting to outperform other methods in predicting patch testing results, suggests that more complex, non-linear approaches may be necessary to capture the intricacies of skin sensitization mechanisms. This highlights the potential of ML in discerning subtle patterns that may not be apparent through traditional statistical analyses. A more widespread and diverse dataset would not only enhance the performance of AI but also address concerns around bias, ensuring that AI-driven diagnostic tools are equitable and effective for all patients, regardless of demographic factors.

Despite the promising results, several limitations were identified across the reviewed studies. Firstly,

most studies had relatively small sample sizes, with eight out of 10 studies including fewer than 250 participants, and only two studies (Cunningham et al. [24] and Adler et al. [18]) including more than 1,000 patients. This limits the generalizability of findings and may lead to overfitting in ML models as many of the studies noted. Secondly, there was a lack of diversity in skin types reported across studies, with eight of our studies not specifying the range of Fitzpatrick skin types included. This is particularly important given that skin reactions can present differently across various skin types, potentially affecting the performance of image-based AI models [27,28]. Additionally, the lack of standardization in methodology across studies makes direct comparisons challenging. Some studies used standard European baseline series allergens, while others used specific sets of allergens, making it difficult to assess and compare the robustness of the models across different allergen panels.

The ethical implications of using AI in clinical practice and industry engagement in this space also warrant attention. As AI tools become more integrated into dermatology, it is crucial to maintain transparency and interpretability in AI models [29]. Clinicians must understand the basis of AI-generated decisions to ensure that these tools complement, rather than replace, clinical judgment. Efforts to increase AI literacy among healthcare professionals, as well as to develop user-friendly AI interfaces, will be essential in fostering the integration of these technologies into routine clinical workflows.

Furthermore, the regulatory landscape for AI in dermatology, and healthcare more broadly, is still evolving. While AI tools show promise, rigorous validation and regulatory approval are needed before they can be fully integrated into clinical practice [30]. Dermatologists, healthcare institutions, and national and international policymakers must collaborate to develop clear guidelines for the safe and effective use of AI in patch testing and other dermatological applications.

Overall, AI holds immense potential to revolutionize the diagnosis of contact dermatitis through more accurate and standardized patch testing methods. However, to realize this potential, further research is needed to address the challenges of standardization, data diversity, model transparency, and regulatory oversight. With concerted efforts, AI can serve as a powerful tool in dermatology, enhancing diagnostic capabilities, improving patient outcomes, advancing precision dermatology, and ultimately contributing to more equitable healthcare delivery [31].

Conclusion:

This narrative review underscores the significant potential of AI to revolutionize patch testing by enhancing diagnostic accuracy, reducing inter-provider variability, and contributing to a more standardized and efficient framework for diagnostics and interpreting patch test reactions from digital images. The high accuracies achieved by CNN models in patch test image analysis are particularly noteworthy, suggesting a possible path towards more standardized and objective patch test interpretation internationally. Our analysis also highlights a need for the development and adoption of standardized protocols for capturing and storing patch test images. Establishing these protocols is crucial for facilitating accurate diagnostics across diverse patient populations, supporting quality improvement efforts, and promoting AI-driven advancements and analyses. The creation of expansive patch testing databases and standardized protocols will empower increased application of AI systems to deliver more accurate, equitable, and scalable care in the management of ACD.

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Abbreviations:

ACD: Allergic Contact Dermatitis

AI: Artificial Intelligence

AUC: Area Under the Curve

CNN: Convolutional Neural Networks

DL: Deep Learning

EMBASE: Excerpta Medica Database

ICD: Irritant Contact Dermatitis

ML: Machine Learning

OVID: Online Variants in Databases

PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses

SD: Standard Deviation

Supplementary Files

Figures

PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 flow diagram for the identification of studies [15].