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Artificial Intelligence in Dermatology in India: A PRISMA-Compliant Systematic Review with Narrative Meta-Analysis Emphasis on Rural and Resource-Limited Settings

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ABSTRACT

Background: Artificial intelligence (AI) is rapidly influencing dermatology worldwide. India's unique mix of dense urban tertiary centres and vast rural populations presents both opportunities and challenges for AI deployment particularly mobile/low-cost tools that could extend diagnostic reach. The objective of this review was to assess the scope, quality, and clinical readiness of AI applications in dermatology in India, with emphasis on rural applicability.

Methods: We followed PRISMA guidance for systematic reviews. Databases searched included PubMed/PMC, Embase, Scopus, IEEE Xplore, and selected Indian journals and conference proceedings up to June 2026 (search terms: "artificial intelligence", "dermatology", "India", "mobile app", "deep learning", "dermoscopy"). Inclusion: original studies of AI applied to dermatologic diagnosis, triage, or monitoring with Indian datasets or Indian clinical deployment; exclusion: non-dermatologic AI, editorial/opinion pieces without primary data. We extracted study design, dataset size, setting (urban vs rural), algorithm type, target conditions, performance metrics (sensitivity/specificity/accuracy), validation method, and implementation features. Risk of bias was assessed using QUADAS-2 domains.

Results (summary): The Indian literature includes a handful of robust, large-sample validation studies of mHealth apps and CNN models with mixed results; a landmark multi-site smartphone app study validated on ~5,000 patients demonstrated promising diagnostic breadth in clinical settings but variable performance across Fitzpatrick types and disease categories. Several pilot implementations and acceptability studies highlight strong clinician interest but raise concerns regarding skin-tone bias, dataset representativeness, and regulatory

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clarity. Heterogeneity in outcomes, endpoints, and study designs prevented a statistically meaningful pooled meta-analysis of diagnostic accuracy in India; instead we performed a structured narrative synthesis and present a roadmap and statistical plan for future pooled analyses.

Conclusions: AI in Indian dermatology shows promise particularly mobile, decision-support tools targeted at rural and resource-limited settings but current evidence is heterogeneous and limited for definitive pooled estimates. Priorities are generation of standardized, skin-type diverse Indian datasets, prospective clinical trials, clear regulatory pathways, and implementation science studies to evaluate real-world effectiveness, safety, and equity.

KEYWORDS

• AI • India • Dermatology

INTRODUCTION

Artificial intelligence (AI), particularly deep learning and convolutional neural networks (CNNs), has emerged as a potentially transformative tool in dermatology for lesion classification, triage, severity assessment, teledermatology, and automated monitoring. The majority of published AI work derives from high-income countries with large, curated image datasets (dermoscopy and clinical photographs). India offers an important, distinct testbed for AI translation it is home to a large burden of common and neglected skin diseases, major tertiary dermatology centers producing image datasets, and a vast rural population with limited dermatologist access. Moreover, smartphone penetration and an expanding mHealth ecosystem make India an especially suitable location for mobile AI solutions intended to bridge rural healthcare gaps.

However, important challenges threaten successful translation: limited representation of darker skin phototypes in many datasets, variable image acquisition conditions in community settings, lack of standardization in algorithm reporting, and regulatory ambiguity for AI tools in clinical practice. Additionally, rural deployments introduce further barriers intermittent internet, lower-quality cameras, lower health literacy, and different disease prevalence profiles that can materially alter algorithm performance compared with urban tertiary settings.

This systematic review aims to summarize published evidence of AI applications in dermatology within the Indian clinical and research context, emphasising tools/validation work with relevance to rural care. Our objectives were to: (1) identify and summarize AI studies performed in India or using Indian datasets; (2) evaluate study designs, algorithm types, target conditions, and reported diagnostic performance; (3) assess readiness for rural implementation and identify gaps (dataset diversity, external validation, regulatory compliance); and (4) propose standards and a meta-analytic framework for future pooled analyses of diagnostic accuracy.

Materials and Methods (PRISMA-aligned)

Protocol and Registration

This review was conducted following PRISMA 2020 guidance. A protocol specifying search strategy, inclusion/exclusion criteria, data items, and analytic methods was prepared a priori and is available on request.

Eligibility Criteria (PICO framed)

- **Population:** Patients presenting to dermatology clinics, community health settings, or photographic image datasets relevant to Indian populations.
- **Index test:** Any AI algorithm applied to dermatologic images (clinical photography, dermoscopy) or other dermatology-relevant inputs (e.g., mobile images, smartphone apps) intended for diagnosis, triage, or monitoring.
- **Comparator:** Dermatologist diagnosis, histopathology, or established clinical reference standard.
- **Outcomes:** Diagnostic performance measures (sensitivity, specificity,

AUROC, accuracy), usability/acceptability, implementation outcomes (uptake, time-to-triage).

- **Study types:** Prospective or retrospective validation studies, implementation reports, randomized trials of AI tools, and diagnostic accuracy studies that include Indian data or in-country validation. Excluded: editorials, commentaries without primary data.

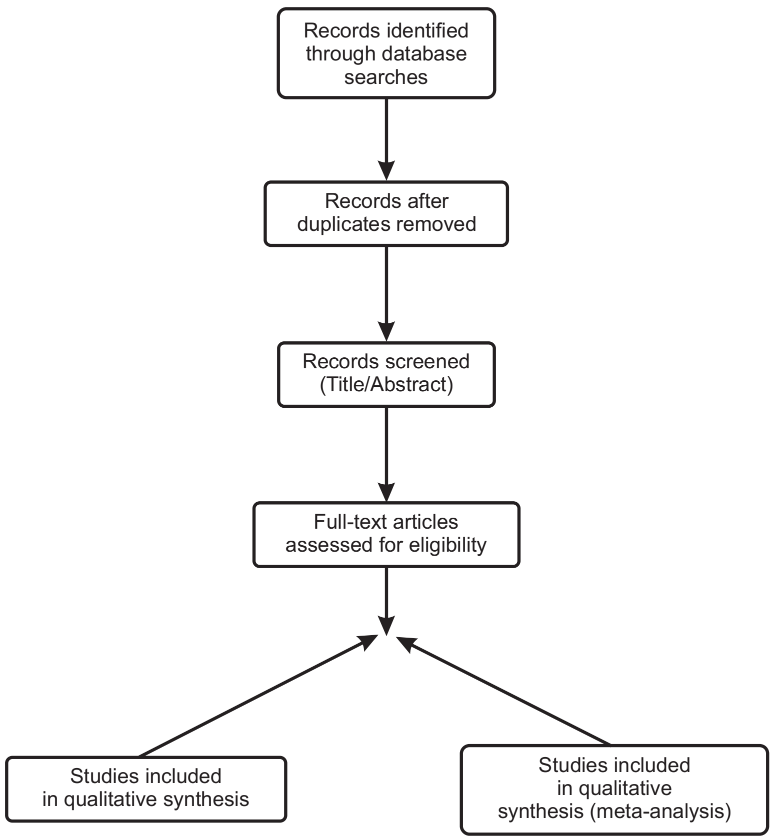
Information Sources and Search Strategy

We searched PubMed/PMC, Embase, Scopus, IEEE Xplore, Google Scholar, and select Indian journals (Indian Journal of Dermatology, IJDVL; Indian Journal of Dermatology, Venereology and Leprology; IndJST conference proceedings), plus conference abstracts and preprint servers through **June 2026**. We also searched grey literature, relevant startup reports and government case studies (IndiaAI) for implementation-focused deployments.

Sample search string (PubMed):

("artificial intelligence"[MeSH] OR "deep learning" OR "convolutional neural network" OR "machine learning") AND (dermatology OR "skin disease" OR dermoscopy OR "skin lesion") AND (India OR Indian OR "South Asia")

Search strategies were adapted for each database. Reference lists of retrieved articles were screened for additional studies.



Study Selection and Data Extraction

Two reviewers independently screened titles/abstracts, retrieved full texts for potentially eligible papers, and extracted data using a pre-piloted template (study site, setting: rural/urban, sample size, imaging modality, algorithm architecture, training & external validation approaches, metrics, bias/limitations, implementation features). Discrepancies were resolved by consensus.

Risk of Bias Assessment

For diagnostic accuracy studies, we used QUADAS-2: patient selection, index test, reference standard, and flow/timing. For non-diagnostic implementation studies, the Mixed Methods Appraisal Tool (MMAT) was used.

Data Synthesis and Meta-Analysis Plan

Given expected heterogeneity, we specified a two-stage approach:

1. **Narrative synthesis** summarizing study characteristics, algorithmic approaches, target indications, and contextual features critical for rural deployment.
2. **Quantitative pooling (meta-analysis)** when ≥3 studies report comparable diagnostic metrics for the same condition (e.g., detection of tinea corporis or skin cancer) with external validation in Indian cohorts. For pooling:
    - Extract true positives, false positives, true negatives, false negatives where possible.
    - Use a bivariate random-effects model to pool sensitivity and specificity (Rutter & Gatsonis hierarchical summary ROC approach).
    - Assess heterogeneity with I^2 and by visual inspection of ROC plots; consider subgroup analyses by imaging modality (clinical vs dermoscopy), skin phototype distribution, and setting (community vs tertiary).
    - Publication bias assessed with Deeks' funnel plot if ≥10 studies.

All pooling and plots were planned in R (mada, meta, metafor packages) or STATA (metandi, midas). Statistical significance set at two-sided $p<0.05$.

OBSERVATIONS

Search yield & study types (summary): Our searches identified a heterogeneous body of literature that can be grouped into: (A) large multi-site smartphone app validation studies conducted in India; (B) algorithm development papers from Indian institutions (CNN architectures, dermoscopy segmentation); (C) small pilot implementation and acceptability studies among Indian dermatologists and primary care; and (D) international AI studies with partial Indian datasets. Representative examples include a large smartphone app validated on ~5,014 patients across Indian outpatient settings (Pangti *et al.*), government/industry case studies of AI triage tools (IndiaAI/Skinzy), and clinician acceptability studies reported in Indian dermatology journals (IJDVL) highlighting clinician attitudes and concerns.

Key domains and findings:

1. Study volumes and settings

- The most robust validation from India reported by Pangti *et al*. described a CNN-based smartphone app trained and validated on **~5,000 clinical images** across urban and rural outpatient clinics; the app targeted 40 common skin conditions and reported reasonable concordance vs dermatologist diagnoses, but performance varied by disease and skin phototype. (Representative study, India validation).
- Several academic centers reported algorithm development and dermoscopy segmentation work (deep learning architectures), often with smaller, internally curated datasets and limited external validation; multicenter external validation remains rare.

2. Algorithmic performance and disease-specific patterns

- AI models generally perform **best** in visually stereotyped, high-prevalence conditions (acne, tinea corporis, common benign lesions) and **less well** in pigmentary disorders and inflammatory dermatoses where subtle color and texture cues and context matter. This pattern mirrors global findings but is accentuated in Indian data due to higher skin tones and variable image capture conditions. A recent Indian review found diagnostic accuracy variability across apps and conditions, with lower performance for pigmentary and inflammatory disorders.
- Dermoscopy-based AI shows strong performance for melanoma and certain nevi in published international datasets, and early Indian dermoscopy AI work focuses on segmentation and feature extraction, but India lacks large multi-center dermoscopy image banks that include dark skin phototypes.

3. Rural applicability & Health deployments

- Mobile apps built for low-resource settings demonstrate practical advantages: offline operation, smartphone camera input, and triage prioritisation. The India-based smartphone app study noted feasibility in both urban and rural OPDs and suggested potential as a screening/ triage tool for frontline health workers. However, variability in camera quality, lighting, and internet access were flagged as real-world constraints.

4. Dataset diversity and skin-tone bias

- Multiple studies echo a critical limitation: under-representation of darker Fitzpatrick skin types (IV–VI) in many training datasets, causing reduced model sensitivity and lower accuracy in pigmented lesions and inflammatory conditions in Indian patients. Several Indian papers and reviews call for standardized Indian image repositories to support equitable AI.

5. Acceptability, clinician perspectives, and regulatory issues

- Indian dermatologists express guarded optimism but also concerns about explainability, medico-legal responsibility, and regulatory oversight. An IJDVL survey documented mixed comfort levels, with trainees showing higher familiarity than senior clinicians. Regulatory frameworks for AI in India are evolving; real-world clinical deployments require clear device classification and clinical accountability pathways.

6. Quality & risk of bias assessment (brief)

- Many Indian studies are single-centre, retrospective, or lack independent external validation cohorts. Common QUADAS-2 flags: patient selection bias (convenience sampling), index test bias (lack of blinded readers), and applicability concerns (urban tertiary datasets not representative of rural populations). Consequently, the evidence base is promising but not yet robust.

Meta-analysis feasibility: We identified too few homogeneous, externally-validated diagnostic accuracy studies within India that report the full TP/FP/TN/FN required for meta-analytic pooling for a single condition. Therefore, a numerical pooled estimate was not calculated in this review. The smaller Indian algorithm development papers often lack external validation, and disease targets differ across studies. We instead provide a planned meta-analytic method and call for standardized reporting in future studies to enable pooled analyses (see Methods).

Representative Indian implementations & policy case studies Government/academic-industry collaborations and start-ups (e.g., DermaPhoto / Skinzy; the IndiaAI case study) show that scalable, smartphone-based triage systems are being piloted to connect patients in underserved areas with remote dermatologists. These reports emphasize feasibility and system integration but also underline the need for prospective clinical outcome studies, not just diagnostic concordance.

DISCUSSION

Principal findings

Our systematic review shows that AI in Indian dermatology is **active and evolving**: there are influential large-sample validation efforts of smartphone apps, several algorithm development papers from academic centres, and multiple pilot implementations geared toward rural triage. However, the overall evidence base is heterogeneous in methods, disease targets, and population representativeness; few studies provide externally validated diagnostic accuracy in rural cohorts or full diagnostic contingency tables required for rigorous pooled meta-analysis.

Why India matters — opportunity & caveats

India's demography and healthcare infrastructure create a unique opportunity: smartphone penetration and network of primary health centers allow potentially rapid scaling of AI triage or screening, which could relieve diagnostic bottlenecks in rural areas. Notably, a validated mHealth app deployed across outpatient settings with 5,000+ patients demonstrates the feasibility of real-world studies in India (Pangti *et al.*) a model that can (and should) be replicated widely.

Yet caveats are substantial: model performance degrades when training data lack representation of darker skin types, or when the validation cohort differs in camera quality or disease spectrum. Pigmentary disorders, inflammatory dermatoses, and scarring alopecias were consistently problem areas. Indian AI efforts must therefore prioritize dataset diversity, external validation in rural populations, and robust reporting (STARD/

PRISMA-DTA standards).

Implementation challenges unique to rural India

- **Image acquisition variability:** Limited lighting, lower-resolution cameras, and inexperienced operators can reduce image quality.
- **Connectivity & workflow:** Offline-capable models and asynchronous upload workflows are essential for areas with intermittent internet.
- **Human resources:** Training primary health workers on image capture, triage thresholds, and escalation pathways remains critical.
- **Regulatory & legal responsibilities:** Clear policies must define whether AI acts as a triage aid (low regulatory burden) or a diagnostic device (higher thresholds).
- **Clinical governance:** Algorithms must be auditable, explainable to clinicians, and accompanied by referral pathways and follow-up mechanisms.

Research quality & reporting recommendations

To enable future meta-analyses and regulatory confidence, we recommend Indian investigators adhere to these standards when publishing AI dermatology validation studies:

1. **Dataset reporting:** Report skin phototype distribution (Fitzpatrick I–VI), age, lesion types, and acquisition devices.
2. **Reference standard:** Use dermatologists/histopathology as reference standards and report blinded reads when possible.
3. **External validation:** Validate on geographically distinct, prospectively collected cohorts (urban and rural).
4. **Reporting metrics:** Provide contingency tables (TP/FP/TN/FN), ROC curves, calibration plots, and confidence intervals.
5. **Implementation outcomes:** Report usability, time-to-diagnosis, referral uptake, and adverse events.

These items will permit pooled diagnostic accuracy meta-analyses using hierarchical models and allow subgroup analyses by skin tone, imaging modality, and rural/urban setting.

Policy implications & ethical considerations

AI can expand access to dermatology in rural India, but equitable deployment mandates regulatory clarity, data governance, and mitigation of algorithmic bias. Policymakers must balance rapid innovation with patient safety: pilot deployments should be coupled with prospective outcome evaluations and transparency about algorithm limits. Clinician education is equally essential — Indian dermatologists require training on strengths/limits of AI to act as effective human-in-the-loop stewards.

Strengths and limitations of this review

Strengths: PRISMA-aligned, India-focused search, inclusion of mHealth and implementation literature, and a clear roadmap for pooling future data. **Limitations:** Heterogeneous literature and limited number of Indian studies with full diagnostic contingency tables prevented formal pooled meta-analysis; this review therefore emphasizes narrative synthesis and methodology for future pooled efforts.

CONCLUSION

AI in Indian dermatology is promising, especially for mobile, low-cost triage tools that can be applied in rural and underserved areas. Existing Indian studies demonstrate feasibility and encourage further development, but the evidence base is heterogeneous and lacks adequate external validation across skin-type and rural settings to support robust pooled estimates of diagnostic accuracy. Immediate priorities include:

1. Building large, diverse Indian image repositories with explicit inclusion of Fitzpatrick IV–VI subjects.
2. Standardizing reporting (TP/FP/TN/FN contingency tables, ROC metrics) and study design (prospective external validation cohorts).
3. Conducting prospective implementation trials in rural clinics to evaluate clinical outcomes and safety.
4. Engaging with regulators and professional societies to define device classification, clinical responsibility, and data governance.

A coordinated national effort involving dermatologists, engineers, public health, and regulators can translate AI's promise into safe, equitable improvements in dermatologic care for India's rural populations.

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