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Mapping Digital Health Technologies for Leprosy in South Asia: A Scoping Review

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ABSTRACT Digital health technologies are increasingly gaining attention as innovative solutions for managing neglected tropical diseases, including leprosy. However, the application of these technologies specifically for leprosy in South Asia remains underexplored. This scoping review aims to systematically map existing literature on digital health interventions targeting leprosy within the region and to categorize these approaches based on their technological frameworks. A comprehensive search was conducted across multiple academic databases, yielding 22 relevant sources, of which 20 were research studies and 2 were public health platforms. The included studies explored a diverse range of digital health tools such as artificial intelligence (AI), mobile health (mHealth), wearable devices, sensors, and public health information systems. These technologies are employed for various critical applications, including early detection of leprosy cases, case management, monitoring nerve damage and ulcers, and enhancing disease surveillance. Notably, AI-based diagnostic models have demonstrated high accuracy, often exceeding 90%, and have been a focal point of research due to their potential to improve early diagnosis and reduce delays in treatment. Mobile health solutions, including teleconsultations, helplines, and SMS-based communication, facilitate patient-provider interactions, especially in remote areas with limited healthcare infrastructure. Wearable sensors and offline data transfer systems are also explored for effective monitoring of nerve damage and ulcer prevention. Despite these advances, the review highlights that other digital intervention areas remain less developed, and the implementation challenges such as infrastructural limitations, connectivity issues, and data interoperability—pose significant barriers, particularly in rural South Asian settings. The review underscores the need for further research to evaluate the long-term effectiveness, scalability, and cost-efficiency of these digital interventions. It also advocates for regional collaboration to bridge gaps in underrepresented countries like Bangladesh, Nepal, and Sri Lanka, ultimately aiming to enhance leprosy control and patient outcomes through technological innovation.

INDEX TERMS Artificial intelligence; Digital health; Leprosy; Mobile health; South Asia.

I. INTRODUCTION

Leprosy or Hansen's disease is a chronic infection caused by Mycobacterium leprae and, less commonly, Mycobacterium lepromatosis. It mostly affects the skin, eyes, mucous membranes, and peripheral nerves. If left untreated, it can lead to severe impairment. Depending on the immune response, lepromatous leprosy has numerous lesions and weak immunity, whereas tuberculoid leprosy has few well-defined lesions and strong immunity. The disease manifests years after exposure and is transferred by respiratory droplets or prolonged close contact. Treatment relies on multi-drug therapy (MDT), which contains rifampicin, dapsone, and clofazimine and has been proven to be helpful in treating the condition. Effective management still depends on prompt care.

Ancient manuscripts from China, India, and the Middle East mentioned leprosy, which dates back to 2000 B.C. [1], [2]. In the Middle Ages, there was a common practice of leper colonies and leprosy was viewed as a moral failing [2], [3]. Armauer Hansen's discovery of Mycobacterium leprae in 1873 changed the disease's perception from a moral failing to a medical disease. Leprosy's global prevalence greatly decreased after the 1980s when the WHO introduced MDT, and the disease was declared eliminated as a public health problem in 2000 [4].

South Asia continues to account for more than half of all leprosy cases globally. India accounted for 107,851 of the 182,815 new cases recorded globally in 2023 [4]. Pakistan (236) has relatively fewer cases. However, Bangladesh (3639), Sri Lanka (1520), and Nepal (2522) also indicate notable prevalence. Even though initiatives like India's National Leprosy Eradication Programme (NLEP) achieved some success, eradication has been more challenging because of factors like poverty, limited access to healthcare, and the impact of COVID-19.

Leprosy is highly stigmatized and causes psychological distress, discrimination, and social exclusion. According to studies done in India, patients exhibit high levels of anxiety and social isolation [5], [6], which are fueled by misconceptions about the disease and its labelling. Rural communities usually delay treatment because they rely on traditional cures or unskilled practitioners [7]. Gender disparities, financial limitations, and limited access to healthcare further obstruct timely care.

In South Asia and other developing countries, digital health has huge potential for addressing healthcare issues. They help to overcome obstacles such as the cost of transportation, isolated areas, and a lack of healthcare facilities.

Digital health tools have proven useful in managing chronic conditions like diabetes and asthma [8], [9]. During the COVID-19 pandemic, these services grew rapidly. Chatbots and virtual support groups have also shown potential as mental health solutions for reducing depression and anxiety [10].

Although leprosy digital health solutions are still in their infancy, global attempts have shown potential [11]. Leprosy and its treatment have already benefited from mobile apps and telemedicine, and South Asia may see similar improvements. However, there is still an absence of studies on digital health specifically for leprosy in South Asia as well as globally. Due to its status as a neglected tropical disease, leprosy may not receive enough funding or attention [3]. The majority of current research focuses on other NTD or more general health issues. While global reviews on digital health for leprosy exist [11], [12], [13], they provide limited coverage of South Asian research, typically including only a few studies from this region. To our knowledge, no review that focuses exclusively on digital health and leprosy exists for South Asia or its individual countries. This study seeks to address this gap by conducting a scoping review of the literature on digital health for leprosy in South Asia. Given the exploratory nature of this topic and the broad range of interventions, a scoping review is appropriate for systematically mapping available literature without restricting studies based on methodology.

This paper is organized as follows: The method for identifying and evaluating relevant studies is given in the Methods section. The Results section includes a summary of the extracted data as well as findings categorized by the used digital health technology. In the discussion, these results are interpreted and the limits of this study are acknowledged. Finally, the study's findings are summarized in the Conclusion.

II. METHODS

This study conducted a scoping review to explore the usage of digital health for leprosy, specifically in the South Asian context. The review's goal was to map existing literature. Specifically, this study addresses the following Population, Concept, and Context (PCC) question: What types of digital health technologies have been implemented or studied for leprosy in South Asia, and how can they be categorized based on their technological approach? No formal review protocol was registered for this study.

A. DEFINITION OF DIGITAL HEALTH

This review defines digital health in line with the World Health Organization (WHO) and U.S. Food and Drug Administration (FDA). The World Health Organization (WHO) defines digital health as "the field of knowledge and practice associated with the development and use of digital technologies to improve health." It includes various domains, including artificial intelligence, big data, blockchain, health information systems, the Internet of Things (IoT), interoperability, and telemedicine [14]. The U.S. Food and Drug Administration (FDA) describes digital health as encompassing "mobile health (mHealth), health information technology (IT), wearable devices, telehealth, telemedicine, and personalized medicine." Digital health technologies use "computing platforms, connectivity, software, and sensors for health care and related uses," spanning applications from wellness monitoring to medical devices [15]. In line with these definitions, this review considered studies involving the use of digital health technologies for leprosy.

B. ELIGIBILITY CRITERIA

Studies were considered eligible if they met the following criteria:

Population & Scope:

a. Conducted in South Asia (India, Bangladesh, Nepal, Pakistan, Sri Lanka), or specifically targeting the South Asian leprosy context.
b. Specifically examines digital health applications for leprosy.
c. For Artificial Intelligence and machine learning, studies that developed or tested models for leprosy.

Study Types Considered:

Pilot studies, case studies, experimental studies, qualitative research, and official reports.

Language & Publication Status:

English-language studies published between 2010–2024 in peer-reviewed journals or official reports by recognized health organizations.

The following types of studies were excluded:
Study Focus:
a. Studies on general healthcare systems that do not specifically reference leprosy.
b. Studies focused on leprosy outside of South Asia.

Study Types Excluded:
a. Reviews: Meta-analyses, systematic reviews.
b. Studies focused solely on biomedical aspects of leprosy without digital health components.
c. Commentaries, expert opinions, and perspective articles.
d. Non-Empirical Studies: Conceptual frameworks, theoretical discussions, or policy recommendations without any data, intervention, or evaluation.

Language Exclusions:
Studies in languages other than English (unless fully translated).

C. SEARCH STRATEGY AND STUDY SELECTION PROCESS

This scoping review was guided by PRISMA-ScR but adapted in certain areas to accommodate the limited availability of indexed literature. The search strategy was intentionally flexible and iterative. Searches were conducted over multiple days (December 17–26, 2024) across multiple sources, including Google Scholar, PubMed, and IEEE Xplore. Search terms were adjusted dynamically based on initial results and emerging keywords. Keyword variations, synonyms, and related actions were explored to expand coverage. Examples of keywords and alternative terms used:
a. Disease-related: Leprosy, Hansen’s disease.
b. Technology: Telemedicine, mHealth, eHealth, Telehealth, SMS, Artificial Intelligence, Machine Learning, Electronic Health Records, Health Information Technology, Blockchain etc.
c. Functions (actions): Sensing, Monitoring, Managing, Recording, Tracking, Screening, Diagnosing.
d. Geographical focus: South Asia, India, Bangladesh, Nepal, Pakistan, Sri Lanka.

IEEE Xplore supports structured Boolean queries, which allowed precise filtering of relevant studies. Example queries are:
a. ("leprosy" OR "Hansen’s disease") AND ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("diagnosis" OR "screening" OR "classification") AND ("South Asia" OR "India" OR "Bangladesh" OR "Nepal" OR "Pakistan" OR "Sri Lanka")
b. ("leprosy" OR "Hansen’s disease") AND ("wearables" OR "sensors" OR "devices") AND ("sensing" OR "monitoring") AND ("South Asia" OR "India" OR "Bangladesh" OR "Nepal" OR "Pakistan" OR "Sri Lanka")

Additional queries explored "blockchain," "electronic health records (EHR)," and "remote monitoring", depending on emerging keywords and study relevance.

Searches in PubMed followed a similar Boolean approach, but indexing differences required adaptations. In PubMed, broader digital health terminology was required to retrieve relevant results. Search queries included terms such as:
a. ("leprosy" OR "Hansen’s disease") AND ("digital health" OR "eHealth" OR "health information technology") AND ("South Asia" OR "India" OR "Bangladesh" OR "Nepal" OR "Pakistan" OR "Sri Lanka")
b. ("leprosy" OR "Hansen’s disease") AND ("telemedicine" OR "mHealth" OR "telehealth") AND ("South Asia" OR "India" OR "Bangladesh" OR "Nepal" OR "Pakistan" OR "Sri Lanka")

Since Google Scholar does not fully support Boolean logic, simplified keyword-based queries were used. To improve relevance and ensure regional coverage, technology-related keywords were combined individually with each country name. Example queries included:
a. "Leprosy digital health South Asia"
b. "Hansen’s disease mHealth India"
c. "Leprosy AI diagnosis Nepal Pakistan"
d. "Leprosy telemedicine Pakistan"
e. "Leprosy AI diagnosis Bangladesh"
f. "Leprosy electronic health records Sri Lanka"

PubMed and IEEE Xplore yielded manageable numbers of targeted results (33 and 14 respectively), all retrieved studies were included in the formal selection process. However, Google Scholar returned thousands of results, many of which were irrelevant. To improve relevance, we manually screened the first 10 pages of results per query. This preliminary relevance screening helped narrow down Google Scholar results to 69 studies. Only studies that met broad relevance were formally included in PRISMA, resulting in 116 records screened in the next stage. A preliminary relevance screening involved, title screening to exclude clearly irrelevant studies, and abstract screening (when necessary) for borderline cases. Importantly, the Google Scholar relevance screening was not a formal part of PRISMA. It was only used to remove clearly irrelevant studies before formal screening began. In some cases, manual screening of references, citation tracking, and forward/backward searching were also applied. A total of 116 studies were identified, and after full-text screening, 20 studies and 2 public health systems met the final inclusion criteria. Unlike the research studies, Nikusth and LeIs were included as public health platforms, identified through published studies [16], [17].

This review primarily included peer-reviewed studies and official health reports, with limited incorporation of grey literature (e.g., NGO reports, government documents, unpublished studies). The selection of studies was limited to

English-language publications indexed in specific databases (Google Scholar, PubMed, IEEE Xplore), which may have resulted in the omission of relevant non-English research and grey literature sources. While this approach ensured source reliability, it may have underrepresented unpublished or regionally reported digital health interventions. The potential impact of these choices is further discussed in the Limitations section.

D. DATA CHARTING

The studies were first categorized based on recurring types of technological approaches. Following this categorization, data charting was tailored to capture the most relevant details within each category. For AI-based studies, we charted details on the models, dataset size, validation methods, and performance metrics. For mobile health studies, we charted the mHealth tool used, objectives, target users, evaluation methods, and findings. For wearable and sensor-based studies, we charted device type, objectives, sensors used, testing methods, and findings. Public health information systems were charted based on system functionality, data collection methods, and accessibility. Studies that did not fall under the above categories were charted based on study objectives, Sample/dataset characteristics, methods, and findings. Studies were categorized based on the type of digital health technology rather than their specific applications or functions.

E. JUSTIFICATION FOR LIMITED REGIONAL SCOPE

Although the review covers the wider South Asian region, the majority of the included papers were from India. This focus may be influenced by the following factors:

a. India is a priority area for study and intervention due to its high leprosy burden.
b. The existence of programs and healthcare efforts in India.
c. The scarcity of published or documented interventions in other South Asian nations.

Although this regional focus may appear biased, it is not the consequence of a deliberate rejection of research from other countries, but rather of the distribution of relevant research. This finding indicates a greater gap outside of India.

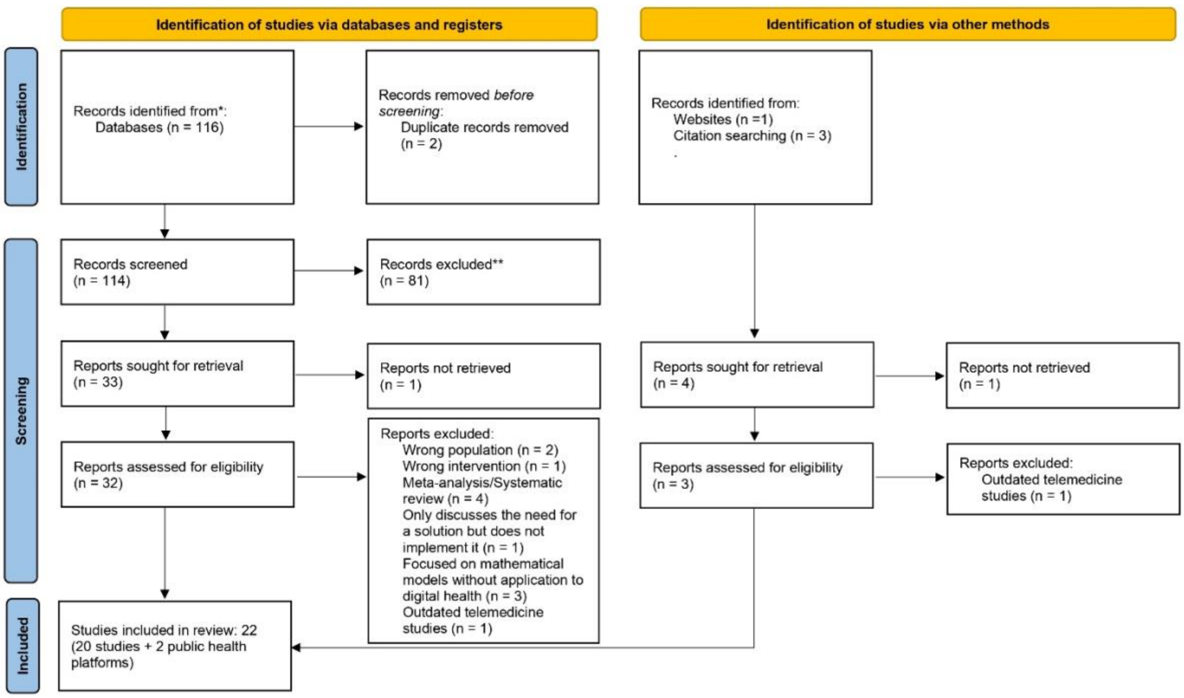

FIGURE 1. **PRISMA flow diagram summarizing the study selection process**

III. RESULTS

A total of 116 records were identified, with 114 studies screened. Following full-text assessment, 20 studies and 2 public health systems were included in the review. Further details on the selection process can be found in the PRISMA flow diagram (FIGURE 1). The majority of inclusions were from India (21), with a contribution of a public health system from Sri Lanka (1). A total of 20 studies and 2 public health systems were analyzed and categorized into five categories: Artificial Intelligence (n=11), Mobile Health (n=3), Wearables and Sensors (n=4), Public Health Information Systems (n=2), and Additional Digital Methods (n=2). The majority of AI-based studies included in this review were published after 2020. The extracted findings are summarized below.

A. ARTIFICIAL INTELLIGENCE

As shown in TABLE I, studies used a wide range of Artificial Intelligence and Machine Learning techniques, including artificial neural networks (ANNs) [18], [19], convolutional neural networks (CNNs) [19], [20], [21], [22], [23], [24], long short-term memory networks (LSTMs) [25], support vector machines (SVMs) [20], [21], [26], logistic regression [24], [26], rule-based classification [26], ensemble learning (AdaBoost, XGBoost, Random Forest) [22], [23], [27], and few-shot learning [28].

The studies utilized mainly two types of data sources, electronic health records (EHRs) [18], [26], [27], and skin lesion images [19], [20], [21], [23], [24], [28]. Several challenges were identified, including data imbalance (in image-based studies) [20], [28], limited data availability [20], [28], the need for model transparency and trustworthiness [20]. Machine learning methods are used in several studies to classify leprosy. According to a study by J. Mehta et al. [26], which compared these algorithms with a rule-based classification method, the rule-based method outperformed the algorithms with a limited dataset, obtaining 94.9% accuracy for other types and 99.2% accuracy for multibacillary/paucibacillary classification. However, J. Mehta et al. [26] imply that machine learning algorithms may outperform rule-based methods when given larger datasets. A different approach by J. Mehta and Kalla [27] used ensemble techniques that include AdaBoost and XGBoost to improve the precision of CART and Random Forest models in predicting the severity of leprosy.

The usage of deep learning models is common. As stated by Jalpa et al. [18], Artificial Neural Networks (ANNs) will likely perform better than other machine learning techniques with larger datasets. H. S. Baweja and Parhar [24] used web-scraped photos and a dataset from DermnetNZ to apply a Convolutional Neural Network (CNN) architecture and obtain 91.6% accuracy in leprosy lesion detection. This CNN architecture was based on Google's Inception-v3 model. J. D. Mehta et al. [25] classified leprosy severity (mild, moderate, and severe) with 99.11% accuracy using a Long Short-Term Memory (LSTM) network optimized with Chicken Swarm Optimization (CHSO). This CHSO-LSTM model performed better than a Particle Swarm Optimization-based LSTM model and other deep learning models such as ANN, GRU, LSTM, and Bi-LSTM. Gawali and Subbulakshmi [21] used multiple CNN architectures, including VGG16, MobileNet v1, Xception v1, and EfficientNetB0, with EfficientNetB0 outperforming the others (accuracy of 0.9138, recall of 0.9298, and F1 score of 0.9217). A study by A. K. Baweja et al. [20] used Explainable AI (XAI) approaches such as Activation Layer Visualization, Occlusion Sensitivity, and Grad-CAM to improve the interpretability of the CNN model LeprosyNet, resulting in 98% accuracy. Jaikishore et al. [19] achieved high accuracy of disease classification (94.32%) and severity prediction (91%), using a modified MobileNetV2 architecture (SkinLesionNet) for skin disease classification and a second model (SeverityNet) for disease severity.

Beesetty et al. [28] explored few-shot learning with a Siamese network to address the problem of data scarcity, with focus on learning from a small number of samples per class. The study also used a hierarchical agglomerative clustering algorithm to subgroup lesions based on morphology.

Some studies combined different techniques. A study by Jitendra et al. [22] used a Random Forest classifier to combine deep features from ResNet101 with GLCM (Gray-Level Co-occurrence Matrix) features. Regions of interest (ROIs) were identified using deep semantic segmentation (UNet), followed by Random Forest classification, GLCM, and ResNet101 feature extraction. Another study applied GLCM and deep features (from AlexNet) for classification after first identifying ROIs using heuristic segmentation [23].

TABLE 1
Summary of AI-Based Studies for Leprosy Diagnosis and Classification

Authors	AI Model Used	Dataset Size and Source	Validation Method	Accuracy and Performance	Clinical Testing?
H. S. Baweja and Parhar [24]	CNN (TensorFlow)	120 images; DermnetNZ, web scraping	Validation accuracy vs. iteration	91.6% accuracy	No
J. Mehta et al. [26]	Rule-based Algorithm, Support Vector Machine (SVM), Logistic Regression	236 patient records; data collected from a web system	10-fold cross-validation	**Rule-Based Algorithm**: 99.2% (WHO), 94.9% (Jopling). **SVM**: 98.7% (WHO), 87.7% (Jopling). **Logistic Regression**: 96.6% (WHO), 83.4% (Jopling).	No

Authors	AI Model Used	Dataset Size and Source	Validation Method	Accuracy and Performance	Clinical Testing?
Jalpa et al. [18]	Artificial Neural Network (ANN), Machine Learning (Logistic Regression, SVM)	Size not mentioned; Bombay Leprosy Project	K-Fold Cross-Validation (k = 3), Train-Test Split (80-20 ratio)	WHO Classification (PB/MB): **SVM**: 98.7% Accuracy (Best), **Logistic Regression**: 96.6%, ANN: 95.83% Ridley-Jopling Classification (6 subtypes): **SVM**: 98.7% Accuracy (Best), **Logistic Regression**: 96.6%, ANN: 95.83%	No
Beesetty et al. [28]	Siamese Network-based Few-Shot Learning (FSL)	396 skin lesion images (368 leprosy, 28 leprosy-simulants)	Sensitivity and specificity metrics, episodic few-shot tasks	Train accuracy: 89.38% - 91.25%, Test accuracy: 73.0% - 73.12%, Sensitivity: 72.39% - 73.66%, Specificity: 69.33% - 77.65%	No
J. D. Mehta et al. [25]	Chicken Swarm Optimized Long Short-Term Memory (CHSO-LSTM), Compared with other models: ANN, GRU, LSTM, Bi-LSTM, PSO-LSTM	3035 electronic health records; collected from an Indian leprosy care center	Train-Test Split: 70%-30%. Performance evaluated using confusion matrix and standard classification metrics	CHSO-LSTM: Accuracy: 99.11%, Precision: 99%, Recall: 99%, F1-score: 99%, MCC: 0.9902, CCE-Loss: 0.019 Outperformed ANN, GRU, LSTM, Bi-LSTM, and PSO-LSTM	No
Jaikishore et al. [19]	SkinLesion Net (based on MobileNet V2), SeverityNet	1524 images; DermNet NZ, CNN-image dataset, web-scraped images	Confusion matrix analysis, performance metrics, cross-validation with different models	**SkinLesion Net**: 94% accuracy for disease classification, **SeverityNet**: 91% accuracy for severity prediction	No
Gawali and Subbulakshmi [21]	EfficientNetB0, VGG16, MobileNet v1, Xception v1	1476 leprosy images (tuberculoid subtype); Kaggle dataset	Split into training, validation, and test sets. Early stopping based on validation accuracy	**EfficientNetB0**: Precision: 0.9138, Recall: 0.9298, F1 score: 0.9217 **VGG16**: Precision: 0.7714, Recall: 0.9474, F1 score: 0.8504 **MobileNet v1**: Precision: 0.9592, Recall: 0.8246, F1 score: 0.8868 **Xception v1**: Precision: 0.8947, Recall: 0.8947, F1 score: 0.8947	No

Authors	AI Model Used	Dataset Size and Source	Validation Method	Accuracy and Performance	Clinical Testing?
A. K. Baweja et al. [20]	LeprosyNet (CNN), compared with AlexNet and ResNet.	Dataset size not specified; Dermnetnz image-based dataset (Kaggle)	80:20 data split (80% training, 20% testing). Performance evaluated using confusion matrix and ROC curve.	**LeprosyNet**: 98% accuracy (Precision: 0.975, Recall: 0.98, F1 Score: 0.975) **AlexNet**: 81% accuracy (Precision: 0.80, Recall: 0.82, F1 Score: 0.80) **ResNet**: 80% accuracy (Precision: 0.80, Recall: 0.80, F1 Score: 0.80)	No
J. Mehta and Kalla [27]	CART, AdaBoost, XGBoost, Random Forest with K-Folds Cross-Validation	250 patient records; EHR database	Cross-validation: 70% for training, 30% for testing. K-Folds Cross-Validation (for Random Forest)	**CART**: 92% accuracy, 95% precision, 92% recall, 92% F1-score **Random Forest with K-Folds**: 95% accuracy, 95% precision, 95% recall, 95% F1-score **AdaBoost**: 97% accuracy, 97% precision, 97% recall, 97% F1-score **XGBoost**: 97% accuracy, 96% precision, 99% recall, 94% F1-score	No
Jitendra et al. [22]	Deep CNN with Semantic Segmentation, GLCM + ResNet101 (Hybrid model), Random Forest for Classification	Not specified	Not specified	Accuracy: 97.24%, Precision: 99.69%, Recall: 95.82%, F-Measure: 0.98	No
Jitendra et al. [23]	Hybrid model combining GLCM features and AlexNet, Random Forest for classification.	220 leprosy lesion images; sourced from hospitals and online platforms	80% training and 20% for cross-validation. Performance was evaluated using statistical parameters (accuracy, precision, recall, F-score).	**GLCM model**: Accuracy = 92.7%, Precision = 89.5%, Recall = 92.1%, F-score = 0.9402 **Hybrid model**: Accuracy = 96.6%, Precision = 99.7%, Recall = 95.8%, F-score = 0.9771	No

[a]ANN = Artificial Neural Network, SVM = Support Vector Machine, CNN = Convolutional Neural Network, FSL = Few Shot Learning, CCE = Categorical Cross-Entropy, GRU = Gated Recurrent Unit, PSO = Particle Swarm Optimization, ROC = Receiver Operating Characteristic, AUC = Area Under the Curve, CART = Classification and Regression Trees, LSTM = Long Short-Term Memory, MCC = Matthews Correlation Coefficient, EHR = Electronic Health Records, AdaBoost = Adaptive Boosting, XGBoost = Extreme Gradient Boosting, GLCM = Gray-Level Co-occurrence Matrix

B. MOBILE HEALTH

As shown in TABLE II, the studies involving mobile phones employed different levels of technological sophistication. Two studies focus on the use of mobile phones to improve communication between healthcare workers and leprosy patients. A study by S. K. Paul and Kumar [29] outlines the uses of simple cell phones and a toll-free number for routine health updates, medication reminders, and patient concerns. Another study conducted in Kolkata used a "missed call"

TABLE 2
Overview of Mobile Health (mHealth) Interventions for Leprosy

Authors	mHealth Tool Used	Objective	Target Users	Evaluation Method	Findings
Lal et al. [30]	Mobile telephony (helpline and call-back).	Improve communication, improve adherence, reduce defaulters, and reduce anxiety	Leprosy patients in Kolkata (urban slums), registered for MDT.	Pilot study, telephonic interviews with 105 patients.	Improved knowledge, satisfaction, early detection, higher TCR (62%), reduced defaulters.
S. K. Paul and Kumar [29]	Mobile handsets (non-android) with call and SMS functionality, toll-free number for communication.	Improve treatment adherence and self-care practices for leprosy patients. Address barriers to treatment. Enhance communication for follow-up and support.	Leprosy patients (newly diagnosed), registered at a tertiary referral hospital in India.	Regular patient interactions via mobile phone. Monitoring treatment adherence, side effects, and self-care practices. Follow-up calls for missed hospital visits and financial support issues.	Increased adherence to treatment through mobile communication. Early identification of financial barriers preventing hospital visits. Improved patient engagement with health workers, preventing default and promoting treatment continuity.
Nikam et al. [31]	AI-based mobile application for leprosy diagnosis.	To develop a cost-effective, quick, and accessible method for diagnosing leprosy through a mobile app.	General population in leprosy-endemic regions (e.g., India), individuals seeking quick leprosy diagnosis.	Usability testing with 15 participants using SUS, primary research via interviews, contextual inquiry, and literature review.	The app was well-received with a SUS score of 80.6.

[a]MDT = Multi-Drug Therapy, TCR = Treatment Completion Rate, SUS = System Usability Scale.

system, which allowed patients to get in touch with supervisors for help and guidance [30]. Nikam et al. [31] propose an AI-based mobile application for diagnosing leprosy. This application would use a smartphone camera to take images of skin lesions, which would then be processed by an artificial intelligence system for detection. The AI algorithm for this system has yet to be developed. The studies employed different data collection and analysis methods. Lal et al. [30] used telephone interviews to assess the impact of mobile counselling, while S. K. Paul and Kumar [29] presented a case report. Nikam et al. [31] used usability testing to evaluate the user interface.

C. WEARABLE AND SENSORS

As shown in TABLE III, all studies in this category focused on measuring pressure distribution. S. Paul et al. [32] explored the usage of textiles with touch sensors integrated to monitor the physical health of leprosy patients. These textiles sense pressure and other mechanical stimuli to determine how patients interact with their surroundings. In a follow-up study, S. Paul et al. [33] developed a tactile sensing glove that measures the peak palmar pressure of leprosy patients. The glove's sensors monitor pressure levels and identify high-risk locations for injuries and ulcers.

A study by Gokhale [34] describes a method for using piezo crystal sensors to measure plantar pressure. The study describes the development and functioning of a sensor system that may be embedded in footwear to measure pressure distribution while walking. The system includes signal processing and data acquisition components. Similarly, Mazumder et al. [35] discuss the development of a wireless insole device that measures foot pressure during various activities. This system offers a graphical user interface for data viewing and wireless data transmission.

TABLE 3
Wearable and Sensor Technologies for Leprosy Monitoring

Authors	Device	Objective	Sensors Used	Testing Method	Key Findings
S. Paul et al. [32]	Sensor-embedded gloves and socks	Monitor nerve and muscle damage, measure pressure distribution, and prevent ulcers in leprosy patients.	Tactile sensors (mechanoreceptors, thermoreceptors, nociceptors), LM35 temperature sensor	Patients wore gloves/socks during daily activities (e.g., cooking, farming), and pressure variations were recorded. Data was analyzed using microcontroller-based systems and statistical tools.	Identified high-pressure areas prone to ulcers.

Authors	Device	Objective	Sensors Used	Testing Method	Key Findings
S. Paul et al. [33]	Tactile sensory glove with embedded pressure sensors	Prevent ulcers and injuries in anesthetic hands of leprosy patients by monitoring pressure distribution.	Flexi Force resistive sensors (thin-film force sensors)	Sensors placed on 9 hand regions using a glove, measured pressure during daily activities (farming, biking, cooking, drinking), Pressure data analyzed.	High-pressure areas identified for different activities, threshold set at 70 kPa to prevent ulcers, real-time auditory feedback (buzzer) helps patients avoid prolonged pressure.
Gokhale [34]	Footwear with pressure sensors (piezocryst-al transducers)	Design footwear to manage foot deformities and prevent ulcers in individuals with conditions like diabetes and leprosy	Piezocrystal transducers, with pressure sensitivity range 500gm to 10Kg	Pressure measurements on foot regions while standing and walking.	Higher pressure on heel and mid-foot in DN group, prolonged stance phase, useful for designing footwear for claw toes, flat feet, and leprosy.
Mazumder et al. [35]	Wireless insole pressure system integrated with capacitive pressure sensors.	Develop a low-cost system to measure and analyze foot plantar pressure during physical activities.	Capacitive pressure sensors placed at four key foot pressure points.	Calibration with varying loads using UTM, followed by real-time testing with a subject wearing the insole during activities like walking and swaying.	Sensor showed a linear response with low hysteresis. Insole system provided real-time pressure data with color-coded feedback.

[a]UTM = Universal Testing Machine.

D. PUBLIC HEALTH INFORMATION SYSTEMS

The National Leprosy Eradication Program (NLEP) in India developed Nikusth, an online reporting tool. Nikusth is based on the District Health Information Software 2 (DHIS 2) platform [16]. This system's goals are to create a nationwide leprosy case database and to produce monthly and yearly reports. Data is first collected on paper forms and then manually entered into the Nikusth system by data entry operators. Data flows from PHCs to districts, then to blocks, and ultimately to the national level.

The Anti-Leprosy Campaign (ALC), a part of Sri Lanka's Ministry of Health, created the LeIS system [17]. This system combines a real-time GIS component with a web-based database (LeIS). Public health inspectors (LC-PHIs) use tablets to enter data directly into a web-based database, which offers near-real-time updates. LC-PHIs send data to district program managers. TABLE IV summarizes the public health information systems.

TABLE 4
Public Health Information Systems for Leprosy Surveillance

System Used	Country	Overall Functionality	Data Collection Method	Accessible to Private Practitioners?
Nikusth	India	Online reporting system; patient tracking; Used to generate monthly and annual reports.	Paper-based initial data entry; manual data entry into the online system by DEOs.	No
LeIS	Sri Lanka	Real-time data entry via tablets, GIS integration, and a user-friendly dashboard for program managers.	Real-time data entry by LC-PHIs using tablets; data from dermatology clinics.	No

[a]GIS = Geographic Information System, LC-PHIs = Leprosy Control Public Health Inspectors, DEOs = Data Entry Operators

E. ADDITIONAL DIGITAL METHODS

As detailed in TABLE V, two studies explored other uses outside of AI, mHealth, wearables and sensors, and public HIS that did not fall within the preceding categories. The study by Kumar et al. [36] focuses on the design and development of a computer-aided orthotic device for offloading plantar ulcers. The study uses computer-aided design (CAD) simulation to create lightweight, aesthetically appealing devices. Agrawal et al. [37] used image processing techniques (thresholding and contour detection) to automate bacterial counting in 44 leprosy skin smear images. Contour detection yielded more reliable bacterial counts than thresholding, with counts varying across different leprosy grading categories (3+ to 6+).

IV. DISCUSSION

The purpose of this scoping review was to identify and compile literature on digital health technologies related to leprosy in South Asia. We aimed to fill the gap in this area. This scoping review identified several leprosy-specific digital health advancements. AI-based methods mostly concentrated on classification models and image-based diagnostics. AI models typically obtained high accuracy (>90%) in classifying leprosy. Studies with mobile health and phone helplines revealed that basic devices like mobile phones could enhance

TABLE 5
Summary of additional digital health methods identified

Authors	Subject Size/Dataset Size	Objective	Method	Findings
Kumar et al. [36]	-	Design a lightweight, customizable offloading device for improving patient compliance and aesthetic acceptance without compromising efficacy.	2D sketches converted to 3D models using SolidWorks. Models tested with ANSYS to simulate pressure distribution. Pressure data was collected using tactile sensors.	Eight models tested, with two designs selected for further development based on effectiveness, weight, and ease of assembly. Prototypes to be tested for long-term efficacy and mechanical behavior.
Agrawal et al. [37]	44 retrospective skin smear images from Schieffelin Institute	Automate bacterial counting and grading for leprosy diagnosis, improving accessibility and efficiency.	Global threshold segmentation and contour detection. SSIM and MSE for performance analysis.	Better performance with contour detection vs. thresholding. Bacterial count ranges: 3+ (82-909), 4+ (115-16712), 5+ (1743-2597), 6+ (6367-15966) SSIM: Max = 0.89, Min = 0.52 MSE: Min = 2138

[a]SSIM = Structural Similarity Index Measure, MSE = Mean Squared Error

patient communication and treatment compliance. Wearable and Sensor-based technology aids in tracking the effects of leprosy, such as nerve damage and ulcers. Public Health Information Systems for leprosy surveillance and case reporting have also been actively supported and used by authorities in India and Sri Lanka.

The increasing use of AI and machine learning (ML) in medical diagnostics is reflected in the selected studies, which predominantly explored AI-driven leprosy detection. ML algorithms have been explored for leprosy classification using EHRs, with accuracy varying by classification criteria and dataset. CNNs have been applied to lesion images, while deep learning models have also been studied for severity prediction, though their real-world applicability remains dubious. Challenges such as dataset limitations, variations in classification methods, and the need for clinical validation remain.

Studies have involved mostly using accessible clinical datasets for model training. Model performance and the ability to differentiate leprosy from other illnesses are influenced by the availability and diversity of datasets. Distinct leprosy types may also have distinct data distributions, with some circumstances being more represented than others. AI models show promise for classification and lesion detection but remain largely limited to algorithm development. Addressing dataset limitations may require strategies such as data sharing, collaboration and data augmentation to improve dataset diversity, while federated learning, and transfer learning could enhance model generalizability. Explainable AI (XAI) techniques, such as those used by A. K. Baweja et al. [20], may help improve model transparency and trustworthiness. Additionally, adhering to defined reporting criteria may improve the veracity of AI studies.

As AI-based diagnostics advance, future research may look into their use in clinical settings. Addressing variances in healthcare environments may be necessary for their incorporation into clinical practice. The healthcare systems in South Asia vary greatly; some regions have strong programs for neglected tropical diseases, while others struggle with a lack of resources and infrastructure. AI-based technologies could supplement current leprosy management strategies, especially in areas where access to specialists is limited. For example, AI-based diagnostic support might be integrated into telemedicine platforms, which allows primary healthcare workers to use automated assessments to make decisions. AI models trained on electronic health records (EHRs) may help with risk assessment, while text-mining algorithms may aid with medical record information retrieval and interpretation [26].

Interventions in mobile health (mHealth) have shown promise in promoting treatment compliance, improving patient engagement, and assisting early identification of leprosy signs. Simple strategies, involving toll-free calls have been effectively used to improve patient follow-up and remove geographic or financial obstacles to care. In parallel, the emergence of AI-integrated mobile applications opens up prospects for improving diagnostic efficiency and accessibility. The growing use of smartphones presents a great opportunity to include automated diagnostic support in digital health strategies. These applications, however, are still at the conceptual stage and need real-world implementation studies and clinical validation. Medical practitioners who are used to conventional, face-to-face consultations could be reluctant to embrace digital alternatives.

AI-based mobile health applications offer the advantage of scalability and adaptability, which makes them well-suited for deployment in low-resource settings. Mobile apps can be optimized for low-end Android devices to ensure broader usability, while local language chatbots and voice-assisted AI features may improve accessibility for those with low literacy levels. Automation and clinical supervision could be balanced via the use of hybrid models, in which patients self-evaluate while medical professionals verify the results. For example, the K Health app [38] during the COVID-19 pandemic combined self-assessment, AI-driven symptom checks, and remote physician consultations. Offline functionality may increase accessibility, as seen in SKINAPP [39], which allows healthcare workers to access essential disease information without an internet connection. For South Asia, comparable offline-compatible mobile health tools might be investigated, that allow community health workers to obtain treatment recommendations in isolated locations.

Additionally, Wearable and Sensor technology may offer an effective method to monitor and prevent impairments in leprosy patients, mainly by identifying irregularities in pressure distribution that may cause ulceration. These approaches seek to provide early warning of possible hazards. This effort eventually promotes self-care practices. Plantar and palmar pressure have been measured using methods, like tactile detecting textiles, wireless insole sensors, and piezo crystal sensors. Sensor durability, data accuracy, and usability are critical for long-term usefulness. To guarantee that devices are utilized efficiently, training is also required for patients and healthcare professionals. Users may need continuous education and support to understand and act upon the feedback they get.

Digital technologies offer the potential to improve leprosy surveillance by easing data collection, transmission, and analysis. The shift from paper-based to totally digital reporting is an ongoing issue. Many areas still use manual data entry, which causes mistakes and delays. These systems as implemented in the public sector, are inaccessible to private sector healthcare workers. Since private-sector health data is not directly incorporated into official public health systems, interoperability issues also hinder the efficacy of these systems. LeIS's reliance on internet connectivity and tablet computers may limit its applicability in areas with poor infrastructure. Nikusth's paper-based initial data entry reduces its dependence on technology but may introduce delays and potential data loss. Most AI-based studies focused on retrospective analysis. Mobile health interventions were primarily designed to facilitate communication between patients and healthcare providers. Sensor-based technologies have been tested in controlled environments. Systems like Nikusth and LeIS were government-led initiatives for disease surveillance.

The distribution of studies across different categories was uneven. A large proportion of the included studies explored AI and machine learning techniques. This may reflect a growing research interest in AI applications for diagnosis, while other digital health approaches appear less frequently studied in recent years.

The identified studies show both similarities and differences when compared to interventions for other neglected tropical diseases (NTDs). For tuberculosis mhealth, while there are obvious parallels between patient engagement strategies and telecounseling, there are also notable variances in terms of implementation level, focus, and difficulties encountered. Compared to leprosy, mobile health for TB have been more developed and extensively researched [48]. When comparing findings to scabies interventions, they have similar goals and focus but may differ in technological usage and integration. More broadly, the findings presented by Barnowska et al. [49] show that scabies and leprosy often co-occur in studies on digital health.

Few studies evaluate the long-term viability of these technologies in practical contexts; most concentrate on model development or pilot implementations. Future studies might explore the scalability and cost-effectiveness of digital health in leprosy prevalent regions. Research on user acceptance, among patients and healthcare professionals, may shed light on the factors that encourage and hinder the use of leprosy specific digital health.

Many rural regions in South Asia still experience issues with internet connectivity and reliable electricity [40], [41]. It may be possible to modify digital health tools to operate within current limitations rather than depending on extensive infrastructural improvements. For example, a telemedicine initiative in Lucknow, India used local doctors as 'carrying agents' to facilitate consultations in spite of network difficulties [42]. Similarly, a study in Bangladesh has investigated the use of low-cost telemedicine hardware using Arduino and Raspberry Pi for reasonably priced remote diagnostics [43]. In rural Liberia, an offline Bluetooth-based data transfer system was created to facilitate communication among community health workers [44]. Given that leprosy-affected regions in South Asia may face similar obstacles, future studies could look into whether lightweight, decentralized digital health models can be adopted for leprosy.

Future research could also explore the long-term impact of mobile health applications on patient adherence, engagement, and health outcomes. Additionally, longitudinal studies on wearable technologies could provide insights into their real-world adoption, usability, and effectiveness. Furthermore, tele-education initiatives could contribute to improving leprosy management by training healthcare workers and raising community awareness. Digital learning approaches may be possible, as evidenced by the inclusion of online training for healthcare workers in India's National Leprosy Eradication Programme (NLEP) [45].

Bangladesh, Nepal and Sri Lanka are underrepresented in digital health research for leprosy, which suggests a need for further regional collaboration. Cross-country collaborations and comparative studies may help to close this gap. Initiatives such as the RESPIRE collaboration [46], which supported multi-country health research, could serve as a model for advancing interventions for leprosy. A relevant example is NLR Nepal's partnership with local, provincial, and national governments [47], which has successfully implemented the Leprosy Post-Exposure Prophylaxis (LPEP) pilot to improve early detection and preventive treatment. Similar collaborative frameworks might be investigated.

A. LIMITATIONS OF THIS SCOPING REVIEW

As a scoping review, this study aims to map existing evidence rather than assess study quality or effectiveness. A formal risk-of-bias assessment was not conducted, and studies were not critically appraised for methodological rigor. Findings should therefore be viewed as an overview of available evidence.The search strategy primarily relied on electronic databases, which may have excluded relevant literature not indexed in these sources. Additionally, the review focused on English language publications, possibly overlooking important research published in regional South Asian languages. This review did not include much grey literature, such as NGO reports, non-scholarly publications, or overlooked government health initiatives, which might have provided valuable implementation insights. Omitting these sources may have led to an incomplete representation of digital health activities in the region. Future reviews may expand coverage by systematically searching grey literature repositories and reviewing NGO or government reports on digital health projects. Although the review aimed to cover South Asia as a whole, most included studies were from India. While this focus is expected, further research is recommended to expand beyond India and include perspectives from countries such as Bangladesh, Nepal, Sri Lanka, and Pakistan. It is also possible that relevant digital health interventions exist in other South Asian countries, but are underreported in indexed literature. Expanding research efforts to these regions through regional studies may provide a more comprehensive understanding.

While telemedicine is a critical component of digital health, this review did not include telemedicine-specific studies for leprosy from South Asia, as the only available research was from 2001 and 2005 [53], [54]. The exclusion was necessary to focus on recent developments, but it highlights a notable research gap.

Unlike a systematic review, this study does not include a meta-analysis or statistical synthesis of digital health interventions. While some studies reported quantitative metrics, the heterogeneity of study designs made it impractical to aggregate results.

V. CONCLUSION

This scoping review mapped the available literature on digital health interventions for leprosy from South Asia. The reviewed studies show diverse applications, with AI-based diagnostic tools showing high accuracy, mobile health interventions facilitating patient communication, wearable and sensor technologies being explored for monitoring nerve damage and ulcer prevention, and public health information systems for disease surveillance. AI-driven diagnostics have received significant attention, while other areas remain less explored, with most research concentrated in India.

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