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Toward Equitable AI Deployment: Overcoming Barriers to Breast Cancer Diagnosis in Rural and Underserved Communities

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Abstract: Early access to breast cancer diagnosis is still a crucial issue in rural and underprivileged areas, where medical infrastructure, specialist presence, and awareness are limited. Although AI models have proved highly accurate in detecting breast cancer utilizing mammography and clinical data, the successful deployment of these tools in low-resource areas poses significant challenges. This paper discusses the most significant hurdles in the adoption of AI-based breast cancer diagnostic systems in rural settings, such as infrastructural gaps in technology, financial limitations, shortages of trained staff, and patient-clinician trust issues. Based on the existing literature, case studies, and public health paradigms, this research also delineates probable strategies to overcome these hindrances, e.g., combining AI with mobile health platforms, IoT-based diagnostic platforms, community health worker training initiatives, and policy-level initiatives to subsidize technology uptake. Through its focus on deployment concerns related to technical performance, the research highlights the avenues that must be pursued to ensure fair access to life-saving AI technology in breast cancer diagnosis and screening.

Keywords: *Artificial Intelligence (AI), Breast Cancer Screening, Rural Healthcare, Implementation Barriers, Mobile Health (mHealth), IoT based Diagnostics, Healthcare Accessibility, Low-Resource Settings, Public Health Technology.*

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I. INTRODUCTION

A. Brief on Rural Healthcare Challenges

Rural regions worldwide have significant healthcare issues, such as poor access to hospitals, a lack of expert doctors, poor diagnostic facilities, and transportation infrastructure. Many rural populations must travel long distances for even basic medical services, leading to delays in diagnosis and treatment. These gaps often lead to delays in identifying critical illnesses, resulting in poorer health outcomes compared to urban populations, especially for time-sensitive conditions like cancer, where early detection is vital [5].

B. Breast Cancer: Prevalence and Rural Diagnosis Delay

Breast cancer is among the common causes of mortality in women, and early diagnosis ensures successful treatment [4], [5]. In rural areas, though, the unavailability of diagnostic tools such as mammography and low awareness levels usually result in late diagnosis, lowering the chances of survival. This delay contributes to increased mortality and reduced treatment options in rural areas.

C. Role of AI in Bridging the Diagnostic Gap

Artificial Intelligence (AI) has become a revolutionary tool in medicine, with great hope in crossing these rural-urban health divides. AI-powered diagnostic algorithms, especially based on machine learning, can help in the early and precise identification of breast cancer based on mammographic or clinical information. These diagnostic systems can be implemented through mobile health (mHealth) devices or telemedicine programs [10], extending expert-level diagnosis to the remotest areas.

D. Need for Accessible Implementation of AI-Based Diagnosis

Considering the persistent gaps in early breast cancer detection and the promising potential of AI to enhance detection rates, there is a pressing need to investigate not only the technical potential of AI models but also the challenges and opportunities in applying these tools to real-world [6], [7], low-resource settings. This research thus seeks to identify barriers to rolling out AI-based breast cancer diagnostic technologies in rural and underserved settings and investigate

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feasible strategies to facilitate equitable access to such life-saving technologies.

E. Research Objectives

This research aims to evaluate the effectiveness of Artificial Intelligence (AI)-modelled diagnoses for breast cancer, utilizing clinical data. Through the application of machine learning on actual medical data, the study hopes to determine how accurately AI can identify benign and malignant cases. The study further examines the viability of applying such AI-based diagnosis tools in rural healthcare facilities, where access to specialist physicians and diagnostic centers is limited. Through this strategy, the paper seeks to show how AI has the ability to minimize diagnostic delay and greatly enhance early detection among the underprivileged communities, hence closing the gap in healthcare between rural and urban areas.

II. LITERATURE REVIEW

Larsen et al. (2024) assessed an AI system on over 600,000 mammograms from Breast Screen Norway. With AUC scores above 0.93, the system showed potential to reduce false positives and triage low-risk exams, supporting more efficient screening programs [8].

Ghasemi et al. (2024) conducted a systematic scoping review on explainable AI (XAI) in breast cancer diagnosis. They emphasized the importance of transparency and trust in AI predictions, introducing methods like SHAP and Grad-CAM to visualize model decisions, especially for CNN-based systems [7].

Tanveer et al. (2025) explored the use of machine learning models for early breast cancer detection using public datasets such as WBCD and MIAS. They compared SVM, RF, ANN, and CNN, concluding that CNNs offered superior accuracy and recall. The study emphasized AI's potential in reducing diagnostic errors and improving early detection outcomes [12].

Gao et al. (2025) analyzed cancer screening behaviors among urban and rural women in Beijing. They found significantly lower screening rates in rural populations, especially among uninsured and less educated women. The study highlights the importance of accessible diagnostic tools in rural healthcare [17].

Wahed et al. (2025) reviewed 32 key studies on AI and breast cancer, finding CNNs to be the dominant model due to high accuracy in classification. They also observed rising global research interest and encouraged integration of AI with clinical expertise to enhance accessibility [18].

A. AI Techniques in Breast Cancer Diagnosis

Artificial Intelligence (AI), especially machine learning (ML) and deep learning (DL), has shown remarkable potential in enhancing the accuracy and speed of breast cancer diagnosis. Among the most commonly used models are Support Vector Machines (SVM), Random Forest (RF), Artificial Neural Networks (ANN), and Convolutional Neural Networks (CNN). CNNs are particularly effective for image-based diagnostics, as they automatically extract hierarchical features from mammograms and histopathological images, thereby reducing reliance on manual interpretation [10], [11].

Comparative studies have found that CNNs outperform other models, achieving accuracies as high as 95.8% with an AUC-ROC score of 97.4% [2], [10], surpassing even expert radiologists in certain diagnostic scenarios [1]. Random Forest and ANN models also demonstrated strong performance, especially with structured, tabular clinical data.

B. Explainability and Trust in AI Models

Despite the promising diagnostic power of AI, the "black-box" nature of many deep learning models poses a challenge for clinical adoption. Explainable AI (XAI) has emerged to address this issue, offering transparency into how models make decisions. Techniques such as SHAP (SHapley Additive exPlanations) and Grad-CAM are widely used to interpret predictions from tree-based models and CNNs, respectively [6], [7].

XAI improves trust among clinicians by enabling them to visualize important features or image regions influencing the model's output. This is particularly important in high-stakes settings like cancer diagnosis, where explainability supports validation, accountability, and patient safety [6], [7].

C. Model Comparison and Performance Metrics

Several studies have performed head-to-head comparisons of ML models using standard datasets such as the Wisconsin Diagnostic Breast Cancer (WDBC) dataset. Metrics like accuracy, precision, recall, F1-score, and AUC-ROC are commonly used for evaluation.

Table 1. Comparisons of ML Models

Model	Accuracy	AUC-ROC	Remarks
CNN	95.8%	97.4%	Best for image-based diagnosis
ANN	92.5%	93.8%	Balanced accuracy, strong recall
Random Forest	91.3%	92.5%	Good with structured data
SVM	89.7%	90.2%	Less effective with image data

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These findings affirm the superiority of CNNs in image recognition tasks like tumor detection, though models like RF and ANN remain valuable for tabular medical records.

D. Deployment Challenges in Rural and Low-Resource Settings

Although AI tools have demonstrated strong performance, their real-world application in rural areas remains limited. Studies highlight significant gaps in infrastructure, such as the lack of internet connectivity [5], trained personnel, and digital devices in rural health clinics [3].

Moreover, rural screening participation is lower, and there is often a delay in diagnosis due to late presentation, lack of awareness, and travel limitations [12], [13]. These factors widen the urban-rural health divide and reduce the impact of existing AI tools when not adapted to the local context [3].

E. Emerging Technologies Supporting AI Deployment

New developments in Internet of Things (IoT) technology have brought with them portable, connected diagnostic devices that can be combined with AI models. For example, handheld ultrasound or thermal imaging machines can send data wirelessly through smartphones to cloud AI systems for quick analysis. These technologies are particularly valuable in remote areas where access to big medical infrastructure is restricted, and have already been tested in some low-resource environments [4], [10], [11].

F. Key Study on Thermalytix-Based Screening

Ghasemi et al. (2024) explored the application of explainable AI (XAI) in breast cancer detection using NIRAMAI's Thermalytix system. The study highlighted how Thermalytix leverages machine learning to analyze thermal imaging data, enabling non-invasive, radiation-free, and privacy-sensitive screening [5], [7].

A notable advantage discussed was the system's portability and potential for mass screening in low-resource settings. The paper also emphasized that explainability techniques—such as visual heatmaps—can help build trust among healthcare workers and patients, which is particularly critical in rural and underserved regions. This aligns closely with the objectives of the present study, especially in examining the feasibility of deploying such tools across varied socio-economic contexts.

G. Ethical and Practical Considerations

Ethical concerns like algorithmic bias, privacy, and data security are prominent in breast cancer AI research. Several papers emphasized that most AI models are trained on datasets lacking diversity, leading to reduced accuracy for minority groups, particularly in rural populations with unique demographics [1], [13], [14], [15].

To ensure fairness, there is a growing need to develop diverse, representative datasets and adopt federated learning techniques to preserve privacy while training AI systems across distributed data sources.

H. Dataset Generalizability and Transferability Challenges

A 2024 study published in PLOS ONE examined the transferability of AI models trained on U.S.-based mammography datasets when applied to diagnostic images from Indian hospitals. The results showed a significant drop in accuracy, particularly among rural patients, due to variations in imaging equipment, demographic characteristics, and environmental conditions [8], [14]. This highlights a persistent issue in AI research: models developed in high-resource contexts may fail to generalize effectively in low-resource or underserved regions. Such findings underscore the importance of region-specific dataset collection and validation, particularly if AI tools like Thermalytix are to be reliably deployed for rural healthcare screening.

I. Research Gaps Identified

Across the reviewed literature, several key gaps were identified in the context of deploying AI-based breast cancer diagnostic tools in real-world settings:

- Limited research on implementation challenges specific to rural and underserved communities
- Limited validation of AI models in rural contexts, where differences in imaging conditions, patient demographics, and infrastructure impact accuracy.
- Lack of studies addressing infrastructural and socio-cultural barriers to AI adoption
- Minimal exploration of strategies to build trust and awareness among local healthcare workers and patients
- Insufficient integration of AI tools with scalable, low-cost platforms such as mobile health (mHealth) or telemedicine

This study aims to address these gaps by shifting the focus from technical performance alone to a more holistic view of accessibility, feasibility, and sustainability. It explores the practical challenges of bringing AI to the field and highlights strategies for deploying these tools effectively in resource-constrained environments [5], [6].

III. METHODOLOGY

A. Research Design

This research utilizes a qualitative and exploratory design to explore the challenges and limitations of deploying AI-based breast cancer diagnostic tools in rural and underserved healthcare environments. As the goal is not to test a hypothesis or develop a new AI model but to learn about systemic, infrastructural, and social barriers, a qualitative design is most suitable.

B. Data Collection

Secondary data were systematically collected from peer-reviewed journals, global health publications, and implementation case studies between 2019 and 2025. The databases Google Scholar, PubMed, IEEE Xplore, and WHO publications were searched for titles and abstracts using keywords such as "AI in breast cancer diagnosis," "rural healthcare," "implementation challenges," and "mobile health screening." A preliminary list of 56 articles was obtained through database searching. Following the application of inclusion criteria (recency, relevance to rural healthcare, and methodological quality), 32 studies remained for critical review. The most representative and highly cited of these works are presented in this paper.

C. Data Analysis

A thematic content analysis approach was applied to analyze the chosen literature [19]. Repeated patterns and themes emerged in relation to major impediments such as infrastructure deficiencies, cost limitations, and trust deficits, and potential solutions. These encompassed mobile health programs, community training initiatives, policy advice, and employment of emerging technologies like IoT-based diagnostic equipment to facilitate AI deployment in low-resource environments.

D. Scope and Limitations

This research centers on AI-enabled breast cancer screening implementation in rural and underserved populations, highlighting in particular the hindrances that constrain implementation and the strategies outlined in the literature for resolving them. The focus is on infrastructural, economic, educational, and policy-related dimensions of implementation. It is based exclusively on secondary data sources, including peer-reviewed health and medical journal articles, public health reports, and international case studies published between 2019 and 2025.

Although the research does not entail primary data collection or experimental assessment, it aims for a detailed thematic review of current research to clarify actual deployment issues. It also takes into account new implementation approaches like mobile health platforms and IoT-based diagnostic devices, which have been promising in resource-poor environments. Follow-up studies can include field-based research or interviews with patients and healthcare professionals to determine the real-world effectiveness, user friendliness, and public acceptance of such technologies in various rural settings.

IV. FINDINGS AND DISCUSSION

This segment highlights the study's main findings derived from thematic analysis of secondary sources. A number of recurring problems found through the analysis impede the adaptation of AI-based breast cancer screening tools to use in rural and underprivileged populations. These challenges have been categorized into five broad barrier themes, each followed by applicable strategies outlined in the literature reviewed. An overview table of such barrier-strategy combinations is presented initially followed by a thorough explanation of each topic.

A. Summary of Key Barriers and Strategies

The table below summarizes the major barriers to implementing AI-based breast cancer screening in rural areas, along with strategies suggested in the reviewed literature to address each challenge.

Table 2. Barriers and Strategies

Barrier	Proposed Strategy
Infrastructure Limitations	Mobile health (mHealth) platforms, IoT-enabled portable screening tools, and cloud-based AI solutions
Lack of Trained Healthcare Personnel	Community health worker training, AI-assisted tools with simple interfaces
High Cost of AI Deployment	Public-private partnerships, government funding, open-source AI tools
Low Awareness and Trust	Awareness campaigns, use of Explainable AI (XAI), human-AI collaboration
Policy and Systemic Gaps	Integration into national digital health frameworks (e.g., Ayushman Bharat, ABDM)

The following sections provide a detailed explanation of each barrier and the corresponding strategies identified through thematic analysis.

B. Barrier 1: Infrastructure Limitations

One of the most significant challenges for the provision of AI-driven breast cancer screening devices to rural and disadvantaged populations is poor infrastructure. Most of these regions experience poor access to electricity, internet, imaging machines, and qualified health practitioners. These deficiencies make it difficult to deploy AI solutions, which in most cases demand cloud computing and diagnostic-level imaging.

To counter these limitations, compact AI technologies such as Thermalytix by NIRAMAI have arisen [5], [10]. This software employs thermal imaging and machine learning to identify breast abnormalities in a non-invasive, radiation-free, and privacy-preserving manner, with no need for costly mammography devices. The technology is compact and has been deployed effectively in urban clinics and NGO-organised rural health camps in India.

➢ *Case Study: NIRAMAI's Thermalytix*

NIRAMAI's Thermalytix platform has been deployed in over 150 centers across India and is increasingly being used in mobile health vans and cancer screening programs. In Tamil Nadu, it has featured in private diagnostic networks and limited outreach activities such as "Pink Express" mobile screening vans, which conduct community-based screenings in villages.

Although the instrument addresses significant infrastructure constraints by requiring only a tablet, thermal sensor, and electricity, its accessibility is still limited in rural Tamil Nadu. The majority of government Primary Health Centers (PHCs) are not yet equipped with this technology, and it is not yet in Tamil Nadu's core public health program.

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➢ *Regional Focus: Making Thermalytix Accessible in Rural Tamil Nadu*

Tamil Nadu's health department has recently unveiled systematic rural cancer screening programs in 12 districts. This offers a timely chance to ramp up AI tools such as Thermalytix to underserved groups. Successful deployment, though, calls for strategies beyond, including:

- Integration into public health schemes such as Ayushman Bharat and Tamil Nadu's rural cancer screening program
- Scaling up mobile screening vans with Thermalytix in rural areas
- Government subsidy or NGO tie-ups to defray the expense of devices and procedures
- Capacity-building training programs for ASHA and ANM workers to operate the device with confidence
- Localized awareness programs to enhance coverage and acceptability of AI screening
- Telemedicine linkage to enable expert review remotely, minimizing dependence on specialists

These interventions can scale up access to AI-based breast screening in Tamil Nadu and be a model for other states.

C. Barrier 2: Lack of Trained Healthcare Personnel

The second significant obstacle to the successful deployment of AI-driven breast cancer screening technology in rural and disadvantaged areas is a lack of trained healthcare professionals. In contrast to urban hospitals, rural health centers tend to have a skeleton staff, usually comprising ASHA workers, ANMs, and a general medical officer. These experts do not receive training on how to use even simplified AI-integrated diagnostic equipment.

Artificial intelligence systems, as much as they have been crafted to serve the non-specialists, still need elementary digital proficiency, procedural knowledge, and self-assurance to operate the device, capture thermal or imaging data appropriately, and read or transmit the AI-produced reports [6], [9]. In most rural settings, personnel are already overwhelmed with routine immunization, maternal health, and infectious diseases control work, with little space for added screening duties without adequate support and capacity building.

In addition, the absence of familiarity with digital health tools and AI technologies usually causes hesitation or distrust among healthcare staff, constraining the use of existing systems even if the infrastructure has been established. In the absence of local champions or regular technical support, these tools are likely to remain underutilized.

➢ *Strategies to Address the Skills Gap*

To overcome this challenge, several strategies can be adopted:

- Localized, short-duration training programs tailored for ASHA and ANM workers to teach basic usage of AI screening tools like Thermalytix, including device handling, patient preparation, and result interpretation.
- Integration of AI tool training into existing state-level health training modules, so that all newly recruited staff are trained at entry-level.
- Use of simplified user interfaces, mobile apps, and step-by-step audio/visual guides in regional languages to ensure ease of use and learning.
- Incentivizing rural health workers for participating in screening activities, making it a recognized and supported part of their workload.
- Establishing a hub-and-spoke model, where village-level health workers capture data and refer cases to a central diagnostic center with internet and expert support.

These solutions can help ensure not only that AI applications are accessible in rural communities, but also that they are utilized by healthcare staff. Developing confidence and capacity among frontline health workers is crucial to the sustainable deployment and long-term success of these applications.

D. Barrier 3: High Cost of AI Deployment

Cost is still a huge hindrance to the broad use of AI-based breast cancer screening technologies in rural and underserved populations. Most AI solutions, including those supplemented with high-end imaging or cloud infrastructure, come with huge costs in hardware, software licensing, data storage, and upkeep. For instance, though devices such as NIRAMAI's Thermalytix are cheaper than the cost of installing full mammography units, their costs of scaling — training, equipment, and support for operations — are nonetheless out of the price range of small clinics or local NGOs.

Rural healthcare systems tend to work under budgetary limitations and minimal public funding. In these environments, even minimum healthcare services are underfunded, and it becomes hard to prioritize and maintain new technologies. AI applications, in turn, might need updates periodically, internet connections for cloud computing, and devices such as thermal cameras or tablets — all contributing to the initial and ongoing expenses [1], [5].

Private diagnostic labs in cities can absorb these expenses through fee-based models. However, in rural settings where low-cost or free healthcare is vital, such financial models are not sustainable. This leaves a gap where AI devices are technically accessible but financially out of reach for the individuals who can benefit from them the most.

➢ *Strategies to Address the Cost Barrier*

- Government Subsidies and Public Procurement: Include AI tools like Thermalytix in public health tenders and offer subsidized procurement for PHCs and district hospitals.
- Public–Private Partnerships (PPP): Collaborate with technology providers and NGOs to share deployment costs, training, and data infrastructure support.
- Donor and CSR Support: Leverage funding from corporate social responsibility (CSR) initiatives, healthcare donors, or global health organizations to fund rural AI deployment.

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- Device Sharing Models: Introduce rotational models where a set of mobile AI devices is shared across multiple PHCs or screening camps.
- Open-Source and Lightweight Models: Promote development of cost-effective, open-source AI models that run on basic hardware without requiring heavy infrastructure or licensing.

These approaches can help bridge the affordability gap and ensure that cost does not prevent life-saving AI tools from reaching the most vulnerable populations.

➢ *Real-World Example*

In Karnataka, Niramai collaborated with NGOs and corporate CSR initiatives to deploy the "Pink Express" — a mobile screening van equipped with the Thermalytix device. With CSR funding, the initiative provided free breast cancer screening in rural districts to hundreds of women who would otherwise have no access. This model illustrates how cost-sharing and mobile deployment can break down financial barriers in low-resource contexts.

E. Barrier 4: Low Awareness and Trust in AI-Based Screening

Even if AI technologies are technically accessible and funded, rural communities exhibit low awareness of breast cancer screening — and even lower awareness of solutions based on AI. This low awareness exists among both patients and healthcare practitioners, contributing to the underutilization of existing tools, such as Thermalytix.

In most rural areas, cultural beliefs, social stigma, and fear of cancer diagnosis discourage women from taking part in screening programs. That AI is used — usually associated with complexity, impersonality, or even mistrust — also discourages participation. If patients do not know how the system operates, or assume it substitutes for the judgment of a doctor, they tend to stay away from the process.

From the provider's perspective, healthcare workers may be skeptical of AI results, particularly when explanations are unclear or there is limited experience with such technology. This would be even more critical in screening instruments where decisions are taken without physical inspection or direct consultation.

➢ *Strategies to Improve Awareness and Build Trust*

- Community Education Campaigns: Use simple, local-language IEC materials and rural outreach programs to explain breast cancer risks and the benefits of early screening [6].
- Trust-Building Through Demonstration Camps: Conduct local screening events where women and health workers can observe the tool in action and ask questions.
- Human-in-the-Loop Approach: Reinforce that AI supports — not replaces — doctors and health workers, making the system feel safer and more acceptable.
- Explainable AI (XAI) Outputs: Use tools that give interpretable results (e.g., heat maps) so that both users and providers can understand how the AI arrives at a conclusion [16].
- Engage Local Champions: Involve community leaders, SHG members, or teachers to promote screening through trusted networks.

These efforts can bridge the cultural and psychological barriers that limit participation in AI-based screening programs, ensuring that trust and awareness grow alongside technological advancement.

➢ *Real World Example*

In Maharashtra, Niramai partnered with women's self-help groups (SHGs) and primary health workers at a local level to conduct community breast health camps in rural villages. The sessions featured live demonstrations of the Thermalytix screening process, Q&A sessions, and the distribution of educational leaflets in Marathi. The role of local influencers facilitated overcoming skepticism, enhancing comprehension of the AI tool, and practically boosting follow-up screening participation.

In Bengaluru, Bruhat Bengaluru Mahanagara Palike (BBMP) government partnered with NIRAMAI to provide free AI-based Thermalytix breast health screening in multiple municipal hospitals and health outreach programs. These efforts—backed by local civic organizations—provided screening facilities at convenient public centers, with the aim of creating awareness among underprivileged communities and proving the non-invasive, radiation-free screening technique. The program assisted in creating community trust by providing the opportunity for women to personally witness the screening process, query the process, and obtain results instantly at public health facilities.

➢ *Policy Recommendation: Collaboration in the Tamil Nadu Context*

Although AI-driven screening tools such as Thermalytix have been successfully rolled out in urban Karnataka with the cooperation of local administrations, no large-scale rural outreach has been reported in Tamil Nadu. Owing to the state's efforts at cancer screening using PHCs and pilot projects, there is a strong likelihood of cooperation for intervention.

It is suggested that NIRAMAI Health Analytix and the Tamil Nadu State Health Department pursue a public–private partnership (PPP) model for rolling out AI-based, radiation-free breast cancer screening camps in rural districts. This can be combined with existing health activities, such as village health camps, women's wellness clinics, and SHG outreach. Through partnerships, Tamil Nadu can scale up equitable access to modern, radiation-free breast cancer screening and gain public confidence in AI-assisted healthcare delivery.

F. Barrier 5: Data Limitations and Bias in AI Models

A second major hurdle in taking AI-powered breast cancer screening to rural environments is the restriction on the data employed for training and validating such models. The vast majority of current AI platforms, including those utilized in breast cancer detection, are trained on well-annotated, hospital-level datasets — in many cases, urban, private, or foreign medical centers. These datasets tend not to

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exhibit heterogeneity in patient populations, imaging conditions, and real-world variability found in rural settings.

Consequently, AI systems can work well in such controlled clinical environments but experience dramatically reduced accuracy when they are implemented in rural communities with varying illumination, reduced device resolution, or heterogeneity of body physiology. Also, datasets could end up underrepresenting the marginalized communities or women who have never had clinical screens, resulting in algorithmic bias and false negatives in said populations.

Yet another hindrance is the unavailability of open-access, region-specific datasets encompassing breast thermal images, patient information, or environmental conditions in rural Indian environments. This hinders the adaptation and validation of AI models for local implementation, especially in states such as Tamil Nadu where outreach in screening is in its developing stages.

➢ *Strategies to Address Data Limitations*

- Open Data Initiatives: Encourage government and academic institutions to publish anonymized breast cancer datasets representing rural and low-income populations [15].
- Federated Learning Models: Use privacy-preserving techniques like federated learning to train AI models on data collected from multiple rural centers without transferring patient information [14].
- Inclusive Data Collection: During screening camps, collect diverse imaging samples from different regions and ethnic backgrounds to build more inclusive models.
- Partnerships with PHCs and NGOs: Collaborate with local health centers and NGOs to gather real-world data that reflects rural screening environments.
- Transparent Model Reporting: Ensure AI tools report not just accuracy but also confidence scores and model behavior under uncertain conditions.

➢ *Dataset Generalizability Issues*

A 2024 study published in PLOS ONE explored the portability of AI models that have been trained on U.S.-based mammography data when applied to images taken in Indian hospitals. The findings indicated a steep decline in accuracy, especially for patients from rural areas, as a result of variations in imaging devices, population demographics, and environmental parameters. This highlights an important problem: AI models tend not to generalize well when applied outside of their training environment, particularly in low-resource or disadvantaged areas. These results highlight the importance of region-localized data gathering and verification, especially if AI software such as Thermalytix is to be applied with confidence to rural healthcare systems.

V. CONCLUSION AND RECOMMENDATION

This study examined the practical and policy-level challenges involved in bringing AI-based breast cancer screening tools—such as NIRAMAI's Thermalytix system—to underserved and rural regions in India. While numerous studies have demonstrated the technical accuracy of AI in early breast cancer detection, including on thermal imaging data, real-world deployment in low-resource areas remains limited due to infrastructural, social, and systemic barriers.

The main findings indicate that successful rural deployment is hampered by digital infrastructure gaps, low affordability, community lack of awareness, and unavailability of region-based clinical data. The 2024 PLOS ONE study supported the alarm that AI models trained in high-resource or global environments tend to underperform in rural environments, citing the pressing need for local data and adaptable deployment methods.

To address these challenges, this paper recommends a multi-layered approach:

- Public–private partnerships between AI innovators (e.g., NIRAMAI) and state health systems to conduct mobile screening camps in rural districts.
- Integration with mHealth and IoT platforms, enabling portable, low-cost diagnostics via smartphones and thermal sensors [1], [4], [9].
- Awareness-building initiatives involving ASHA workers, SHGs, and local influencers to build trust and encourage participation [16].
- Policy incentives and funding models that support scalable deployment in low-resource settings.

Lastly, although this analysis was based on secondary data and literature review, future research may include primary fieldwork in the form of rural Tamil Nadu surveys or interviews to measure awareness, acceptability, and barriers from the end-user's point of view.

With continued emphasis on data inclusivity, community outreach, and collaborative implementation, AI has the potential to democratize breast cancer screening and close key healthcare gaps in rural India.

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