Next-Generation AI for Breast and Prostate Cancer Diagnosis in Bangladesh: An Implementation Framework and Validation Roadmap

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ABSTRACT

Breast cancer is the most frequently diagnosed cancer among women in Bangladesh, while prostate cancer is an increasing health concern among older men, contributing to a growing national cancer burden. Although artificial intelligence (AI) has demonstrated promising performance in breast imaging and prostate magnetic resonance imaging, most existing models have been developed and validated in high-income settings, limiting their direct applicability to Bangladesh because of differences in disease patterns, imaging quality, clinical workflows, infrastructure, and resource availability. This article proposes a context-specific three-tier AI implementation framework designed to support safe and effective breast and prostate cancer diagnosis in Bangladesh. The framework was developed through a synthesis of AI implementation literature, Bangladesh-specific healthcare challenges, internationally recognized reporting and evaluation standards (STARD-AI, CLAIM, CONSORT-AI, DECIDE-AI, and FUTURE-AI), and WHO guidance on ethical AI. It consists of edge-based AI triage for district hospitals, multimodal clinical decision support for tertiary care centers, and a federated learning infrastructure that enables continuous model improvement while preserving institutional data privacy. A staged validation roadmap, including retrospective validation, prospective silent evaluation, clinical implementation, pragmatic trials, and post-deployment monitoring, is proposed to ensure safety, transparency, and clinical reliability. Rather than replacing clinicians, the framework positions AI as an assistive technology that could strengthen early cancer detection, optimize specialist resources, and support scalable implementation across Bangladesh and similar low- and middle-income countries following rigorous local validation.

Keywords: Artificial intelligence, Breast cancer diagnosis, Prostate cancer diagnosis, Bangladesh, Federated learning, Clinical validation

INTRODUCTION

In Bangladesh, diagnosing cancer is challenging because patients often seek care late, screening is hard to access, radiology services are not evenly available, referral systems are fragmented, and there are not enough trained specialists. These issues are especially significant for breast cancer, which is the most common cancer among Bangladeshi women, and for prostate cancer, which is still underdiagnosed but becoming more important as people live longer. According to GLOBOCAN 2022, there were 12,989 new breast cancer cases and 2,335 new prostate cancer cases in Bangladesh. However, these numbers are partly based on modeled data since the country has limited coverage from population-based cancer registries (Bray et al., 2024; Ferlay et al., 2024).

Early and accurate diagnosis is essential for improving cancer outcomes. For breast cancer, mammography, ultrasound, biopsy, histopathology, and immunohistochemistry form the core of diagnostic evaluation. For prostate cancer, prostate-specific antigen testing, digital rectal examination, multi-parametric MRI, PI-RADS interpretation, targeted biopsy, and histopathological grading inform clinical decisions. In many Bangladeshi settings, diagnostic pathways are often delayed due to cost, distance, limited equipment, inconsistent image quality, lack of expert interpretation, and social barriers such as stigma and fear.

AI offers a potential solution because it can identify imaging patterns, prioritize suspicious cases, support radiologist workflow, and provide standardized risk estimation. In breast imaging, international studies have shown that AI can reduce reading workload and support cancer detection (McKinney et al., 2020; Lang et al., 2023). In prostate MRI, the PI-CAI study showed that AI can achieve expert-level performance for clinically significant prostate cancer detection under controlled validation conditions, while still requiring prospective clinical validation before routine deployment (Saha et al., 2024). These findings are encouraging, but their direct applicability to Bangladesh is uncertain. Differences in scanner types, acquisition protocols, image quality, patient demographics, and disease stage at presentation, health-system capacity, language, digital infrastructure, and governance standards create a need for locally adapted AI systems. The rationale for locally adapted AI systems is also supported by previous work on AI-enabled cancer prognosis, predictive analytics, and decentralized diagnostic support. Prior studies have emphasized that AI systems in oncology should not be treated only as technical tools, but as clinically supervised decision-support systems requiring validation, contextual adaptation, explainability, and integration into real-world healthcare workflows (Tasnim et al., 2025; Rahman, 2017; Rahman & Akhter, 2022).

Artificial intelligence continues to reshape digital technologies through intelligent automation, distributed computing, and advanced data-driven decision-making across multiple domains. Recent studies have highlighted the growing role of AI in intelligent information management, cloud-enabled healthcare systems, and emerging computational platforms capable of supporting complex analytical tasks (Ganapathy et al., 2020; Khan et al., 2021; Sharma et al., 2021). These technological advances provide an enabling foundation for developing scalable, interoperable, and context-aware AI solutions that can be adapted to strengthen cancer diagnosis and clinical decision support in resource-constrained healthcare environments.

Establishing an AI diagnostic system is essential at the national level. Now, the focus should be on presenting an implementation framework and a validation roadmap designed to meet an international standard (Heidary et al., 2021; Li et al., 2021). This strategic pivot not only bolsters scientific credibility and avoids unverified clinical claims but also positions the article as a valuable, hands-on resource for advancing AI-driven cancer control in low-resource environments.

STATEMENT OF THE PROBLEM

Despite significant advances in artificial intelligence (AI) for cancer diagnosis, the translation of these technologies into routine clinical practice remains limited in many low- and middle-income countries, including Bangladesh. Most AI-based diagnostic systems have been developed and validated using datasets, healthcare infrastructures, and clinical workflows from high-income countries, raising concerns regarding their generalizability to resource-constrained settings. Bangladesh continues to face substantial challenges related to limited specialist availability, fragmented health information systems, inconsistent imaging quality, inadequate digital infrastructure, and the absence of standardized AI governance mechanisms. Previous studies have emphasized that effective implementation of health information systems in Bangladesh requires strategic planning, institutional readiness, and integration with existing healthcare processes (Hoque et al., 2016). Similarly, AI-enabled digital health applications have demonstrated the potential to improve patient management and healthcare accessibility, but their successful implementation depends on context-specific adaptation rather than direct technology transfer (Hoque et al., 2020).

Recent advances in AI-driven medical imaging, clinical genomics, robotic diagnostic pipelines, and decentralized clinical decision support have created new opportunities for improving early cancer detection and precision medicine (Ahmed et al., 2020; Asha et al., 2021; Rahman et al., 2025; Rahman & Akhter, 2022). Furthermore, lightweight neural network compression techniques have expanded the feasibility of deploying AI models on edge devices, making AI-assisted diagnosis increasingly suitable for rural and resource-limited healthcare environments (Nusaiba et al., 2023). However, ethical considerations, algorithmic transparency, human oversight, and regulatory accountability remain essential prerequisites for responsible AI deployment in clinical settings (Khan & Fadziso, 2020). Healthcare leadership and organizational readiness also play critical roles in facilitating digital transformation and sustainable AI adoption within healthcare institutions (Shinwary & Rahman, 2024).

Although these studies collectively highlight the technological potential and implementation requirements of AI in healthcare, there remains no comprehensive framework specifically designed to guide the safe implementation, validation, governance, and nationwide deployment of AI-assisted breast and prostate cancer diagnosis in Bangladesh. This gap underscores the need for a context-specific implementation framework supported by a structured validation roadmap that aligns technological innovation with clinical practice, ethical principles, and the realities of the Bangladeshi healthcare system.

RATIONALE FOR A BANGLADESH-ADAPTED AI FRAMEWORK

Medical AI tools usually show good results on retrospective datasets, but they often do not work as well in real world care, especially in new populations or health systems. This problem is even greater in low- and middle-income countries (LMICs), where imaging equipment varies, health records may be incomplete, internet access is not always reliable, and there are not enough specialists. AI models trained on carefully selected data from high-income countries may not be accurate in places like Bangladesh, particularly if the local population differs in age, breast density, disease stage, other health conditions, imaging quality, or referral patterns.

Earlier research by the author and collaborators has similarly highlighted the importance of developing AI-based diagnostic systems that are population-sensitive, clinically

interpretable, and suitable for resource-constrained healthcare environments (Rahman, 2020; Kundavaram et al., 2018; Addimulam et al., 2021; Tasnim et al., 2025). These studies support the present framework's emphasis on local validation, human oversight, ethical governance, and implementation feasibility before AI tools are introduced into routine cancer diagnosis.

A Bangladesh-adapted AI framework should follow five key principles. First, clinical use cases must be specific and measurable, such as mammography triage, mpMRI decision support, or prioritizing high-risk cases for specialist review. Second, local validation is required before clinical implementation. Third, AI output should assist clinician decision-making but not replace histopathology or expert judgment. Fourth, data governance must protect patient privacy and ensure institutional ownership. Fifth, post-deployment monitoring should identify model drift, bias, false negatives, and unintended workflow impacts.

Table 1: Bangladesh-specific barriers and implementation responses

Barrier in Bangladesh	Risk for AI implementation	Design response in the revised framework
Limited radiologist and oncologist availability outside major cities	AI may be used without adequate human supervision if framed as autonomous diagnosis.	Use AI as triage and second-reader support only; require radiologist or trained clinician oversight for high-risk outputs.
Variable image quality and heterogeneous equipment	Model performance may decline when applied to low-quality mammograms, ultrasound images, or mpMRI scans.	Include scanner metadata, quality-control flags, site-stratified validation, and image-quality rejection rules.
Fragmented records and incomplete pathology linkage	False assumptions about ground truth may lead to biased model evaluation.	Create a minimum dataset standard linking imaging, pathology, clinical features, treatment, and follow-up.
Unreliable power and internet connectivity	Cloud-dependent systems may fail during routine service delivery.	Deploy edge-first inference at district sites with offline mode and delayed synchronization.
Low AI literacy among clinicians and patients	Poor trust, over-reliance, or rejection of AI recommendations.	Provide XAI dashboards, clinician training, patient communication tools, and no-blame error reporting.
Unclear regulatory and liability pathways	Unsafe deployment and weak accountability.	Require ethics approval, clinical governance, model version control, audit trails, and alignment with medical device principles.

EVIDENCE BASE FOR AI-ASSISTED BREAST AND PROSTATE CANCER DIAGNOSIS

Breast cancer imaging

Artificial intelligence (AI) applications in breast cancer diagnosis encompass mammography screening, ultrasound classification, MRI interpretation, digital pathology, risk prediction, and workflow triage. Convolutional neural networks and transformer-based architectures have achieved high diagnostic performance in retrospective datasets. An international evaluation by McKinney and colleagues demonstrated that a deep learning system reduced false positives and false negatives in screening mammography

compared with radiologist interpretation under study conditions (McKinney et al., 2020). The MASAI randomized trial further demonstrated that AI-supported mammography screening reduced radiologist screen-reading workload by approximately 44% while maintaining cancer detection safety in an organized screening setting (Lang et al., 2023).

These findings suggest that AI-assisted mammography could be useful in Bangladesh, but it is not ready for immediate adoption. Unlike Sweden or the United Kingdom, Bangladesh does not have a nationwide mammography screening system. Many women only seek care when they already have symptoms, so imaging often happens after a lump is found. Because of this, the first use of AI in Bangladesh should focus on practical triage and decision support, not on large-scale autonomous screening. A good starting point would be to help prioritize suspicious mammograms, support quality checks, and speed up reporting, while still using histopathology as the main diagnostic standard (Rahman, 2020; Kundavaram et al., 2018; Addimulam et al., 2021).

Prostate cancer MRI

AI tools for diagnosing prostate cancer mainly use mpMRI and biparametric MRI. Their main goals are to detect clinically significant prostate cancer, reduce unnecessary biopsies, standardize PI-RADS readings, locate lesions, and help plan targeted biopsies. The PI-CAI study showed that AI systems could match or sometimes even outperform radiologists in detecting clinically significant prostate cancer on MRI (Saha et al., 2024). Still, the study's authors stressed that more real-world testing is needed before these tools are used in clinics. This is especially important in Bangladesh, where access to prostate MRI, consistent scanning protocols, and radiologist experience can differ from one hospital to another.

A Bangladesh-specific prostate AI strategy should initially be implemented in tertiary centers where multi-parametric MRI, pathology confirmation, and urology collaboration are accessible. Early deployment at the district level is not recommended until image acquisition and specialist review processes are standardized. Model evaluation should include not only area under the curve, sensitivity, and specificity, but also rates of biopsy avoidance, incidence of missed clinically significant cancer, time to diagnosis, clinician confidence, and patient acceptability.

Reporting and governance standards

International standards for medical AI have advanced rapidly. STARD-AI supports transparent reporting of AI diagnostic accuracy studies, including dataset practices, index test description, evaluation, bias, and generalizability (Sounderajah et al., 2025). CLAIM provides a medical imaging AI checklist that addresses data, modeling, evaluation, reproducibility, and clinical relevance (Tejani et al., 2024). CONSORT-AI and SPIRIT-AI guide clinical trial reports and protocols involving AI interventions. DECIDE-AI addresses early-stage clinical evaluation of AI decision-support systems (Vasey et al., 2022). FUTURE-AI emphasizes fairness, universality, traceability, usability, robustness, and explainability across the AI life cycle (Lekadir et al., 2025). WHO ethics guidance and Good Machine Learning Practice principles further emphasize human autonomy, safety, transparency, privacy, and continuous monitoring (World Health Organization, 2021; US Food and Drug Administration et al., 2021).

It is important for the Bangladeshi AI concept to clearly state which standard reporting guideline it follows. For diagnostic accuracy studies, STARD-AI and CLAIM are the most relevant. If the concept describes a clinical trial, use CONSORT-AI. For trial protocols, follow SPIRIT-AI. For early implementation or usability evaluations, DECIDE-AI and FUTURE-AI are suitable.

PROPOSED THREE-TIER AI FRAMEWORK

The proposed framework is designed for gradual adoption across the Bangladeshi health system. It avoids a one-size-fits-all approach and separates low-resource triage, tertiary diagnostic support, and national learning infrastructure.

Table 2: Three-tier implementation framework for Bangladesh

Tier	Clinical setting	Primary function	Data inputs	Required human oversight	Minimum validation requirement
Tier 1: Edge-enabled triage	District hospitals, rural cancer centers, mobile diagnostic camps	Flag suspicious breast images for referral and prioritize urgent review	Mammography or ultrasound image, age, symptoms, basic risk factors	Trained clinician or radiographer; remote radiologist review for positive or uncertain cases	Local silent prospective validation with sensitivity prioritized and false-negative audit
Tier 2: Multimodal diagnostic support	Tertiary hospitals, cancer centers, academic medical centers	Assist radiologists and oncologists in mammography, mpMRI, biopsy targeting, and pathology correlation	Mammography, mpMRI, ultrasound, pathology, PSA, clinical examination, EHR variables	Radiologist, oncologist, urologist, pathologist, multidisciplinary tumor board	External validation by site, subgroup, scanner, and disease stage; calibration and decision-curve analysis
Tier 3: Federated learning and national analytics	National cancer network and divisional hubs	Enable model improvement without raw data transfer and monitor performance over time	Model updates, de-identified metadata, outcome metrics, audit logs	National AI governance committee, institutional data stewards, ethics boards	Federated performance comparison, privacy audit, fairness audit, post-market monitoring

Tier 1: Edge-enabled triage

Tier 1 is intended for settings with limited specialist availability. It should not provide a final diagnosis. Its purpose is to reduce delay by identifying images or patients who require urgent specialist review. Lightweight models such as MobileNet, EfficientNet-lite, or compressed CNNs can be deployed on low-cost edge hardware. The interface should display a risk category, confidence estimate, image-quality warning, and explainability map. Low-confidence and poor-quality studies should be automatically referred for human review rather than classified as negative.

The proposed edge-enabled and multimodal decision-support approach is consistent with prior work on digital health platforms, decentralized diagnostics, and real-time clinical decision support (Rahman, 2017; Rahman & Akhter, 2022). These earlier contributions support the use of AI as an assistive tool that can improve accessibility, triage efficiency, and diagnostic coordination while preserving clinician responsibility for final decision-making.

Tier 2: Multimodal diagnostic support

Tier 2 supports tertiary cancer centers and academic hospitals. It can combine imaging with clinical variables such as age, family history, symptoms, PSA density, digital rectal examination, biopsy findings, and pathology markers. For breast cancer, the system may

support BI-RADS assessment, lesion localization, biopsy prioritization, and pathology correlation. For prostate cancer, it may support PI-RADS interpretation, clinically significant cancer probability, lesion localization, and biopsy planning. The system should record when clinicians accept, modify, or reject AI suggestions, because these interaction data are essential for safety monitoring and model improvement.

Tier 3: Federated learning and national analytics

Tier 3 addresses the ethical and practical problem of data sharing. Many hospitals may be unwilling or unable to transfer raw patient data to a centralized repository. Federated learning allows participating sites to train shared models by exchanging model updates rather than raw data. This approach is not a complete privacy solution by itself; it still requires secure aggregation, differential privacy where appropriate, governance agreements, audit logs, cybersecurity controls, and independent oversight.

However, it offers a realistic pathway for Bangladesh because it respects institutional data sovereignty while enabling national learning.

DATA PIPELINE AND MODEL DEVELOPMENT REQUIREMENTS

A credible AI manuscript must describe the complete data pipeline. The dataset should be assembled with clear inclusion and exclusion criteria, patient-level identifiers for de-duplication, source site, acquisition date, scanner type, image modality, lesion annotation method, pathology reference standard, and follow-up period. The dataset should be split at the patient level, not the image level, to avoid information leakage. A hold-out test set should be separated before model tuning. External validation should be performed on at least one site not used during model training.

Table 3: Minimum validation and reporting items for a credible AI diagnostic manuscript

Domain	Minimum item to report before journal submission or deployment
Study design	State whether the work is retrospective, prospective silent validation, randomized trial, implementation study, or framework article. Avoid mixing completed-results language with proposal language.
Ethics and consent	Provide IRB/ethics approval numbers, consent or waiver details, data protection measures, and governance approvals.
Dataset integrity	Report patient counts, image counts, site counts, date range, exclusion criteria, missing data, and patient-level de-duplication.
Reference standard	Use pathology, expert consensus, or follow-up definitions; describe how disagreements were resolved.
Model transparency	Report architecture, preprocessing, training/validation/test split, thresholds, hyperparameters, versioning, and code availability when possible.
Statistical analysis	Report confidence intervals, subgroup performance, calibration, decision curves, inter-reader comparison, and error analysis.
Clinical workflow	Describe where AI appears in the pathway, who sees the output, how overrides occur, and how errors are reported.
Safety monitoring	Include false-negative audit, drift monitoring, bias monitoring, cybersecurity, and human-in-the-loop governance.

For breast cancer, minimum metadata should include age, symptoms, prior imaging, breast density, mammography view, BI-RADS category, ultrasound correlation if available, biopsy result, histological subtype, grade, ER/PR/HER2 status where available, and final clinical stage. For prostate cancer, minimum metadata should include age, PSA, PSA density, DRE findings, MRI protocol, PI-RADS category, prostate volume, lesion

zone, biopsy method, Grade Group, and clinically significant cancer definition. Missing data should be reported transparently and handled using predefined statistical methods.

When reporting a model, provide details on its architecture, software environment, preprocessing steps, data augmentation, hyper parameters, training duration, random seeds, loss function, class imbalance strategy, calibration method, operating threshold selection, and version control. Report performance metrics with confidence intervals, including sensitivity, specificity, positive and negative predictive values, AUC, calibration, decision-curve analysis, false-negative review, and subgroup analysis. Whenever possible, include subgroup results for rural and urban sites, age groups, breast density categories, scanner types, and socioeconomic groups.

VALIDATION AND EVALUATION ROADMAP

The successful implementation of AI for breast and prostate cancer diagnosis requires a structured validation process that extends beyond retrospective model performance. Before AI systems can be integrated into routine clinical practice in Bangladesh, they should demonstrate technical robustness, clinical safety, workflow compatibility, and measurable patient benefit under local healthcare conditions. A staged evaluation strategy minimizes the risk of premature deployment by generating progressively stronger evidence at each phase, from retrospective validation to prospective clinical implementation and long-term post-deployment surveillance.

The safest pathway for Bangladesh is staged evaluation. Each stage should have predefined criteria for continuation, modification, or termination. The roadmap below is designed to generate evidence suitable for policy adoption rather than relying on isolated retrospective model performance. The proposed validation and evaluation roadmap is summarized in Table 4.

Table 4: Proposed staged validation roadmap

Stage	Purpose	Design	Primary outcomes	Go/no-go criteria
Stage 1: Retrospective local validation	Determine whether existing or newly trained models generalize to Bangladeshi data.	Multi-site retrospective dataset with patient-level split and external hold-out site.	AUC, sensitivity, specificity, NPV, calibration, subgroup performance.	Proceed only if sensitivity and calibration are acceptable across sites and false-negative patterns are explainable.
Stage 2: Silent prospective validation	Assess performance in real workflow without influencing patient care.	AI runs in background while clinicians follow standard care.	Prospective accuracy, processing time, missing data rate, image-quality rejection rate.	Proceed only if performance remains stable and no systematic subgroup harm is detected.
Stage 3: Early clinical evaluation	Assess usability, safety, workflow fit, and clinician interaction.	DECIDE-AI aligned implementation study with human-in-the-loop outputs.	User acceptance, reporting time, override rate, error reports, trust, workload.	Proceed only if clinicians understand the tool and unsafe over-reliance is not observed.
Stage 4: Pragmatic trial	Measure patient and system-level impact.	Cluster randomized, stepped-wedge, or controlled before-after study.	Time to diagnosis, early-stage detection, biopsy avoidance, missed cancer, cost-effectiveness.	Proceed to scale-up only if clinical benefit outweighs harms and costs.

Stage	Purpose	Design	Primary outcomes	Go/no-go criteria
Stage 5: Post-deployment monitoring	Maintain safety after scale-up.	Continuous audit with model version control and drift monitoring.	Calibration drift, false negatives, subgroup performance, latency, complaints, security incidents.	Update, pause, or withdraw model if performance deteriorates or safety thresholds are crossed.

CLINICAL WORKFLOW INTEGRATION

AI integration should begin with workflow mapping. A breast cancer pathway may include registration, imaging, AI quality check, AI triage score, radiologist interpretation, biopsy decision, pathology confirmation, staging, and treatment referral. A prostate cancer pathway may include PSA assessment, clinical examination, mpMRI, AI-assisted risk estimation, radiologist review, targeted biopsy decision, pathology confirmation, and multidisciplinary planning. At each step, the accountable clinician must be defined.

The AI interface should be simple. It should show a risk category, probability estimate, confidence range, heatmap or lesion localization, and a recommendation such as routine review, urgent review, repeat imaging because of poor quality, or specialist referral. The dashboard should avoid excessive automation. It should make uncertainty visible and should record clinician response. In Bangladesh, the interface should support English and Bangla terminology for patient-facing explanations, but medical decision outputs should remain standardized to internationally accepted classifications such as BI-RADS and PI-RADS.

Training is as important as model performance. Radiologists, oncologists, urologists, pathologists, sonologists, radiographers, nurses, and administrators should receive training on AI strengths, limitations, false positives, false negatives, data privacy, and error reporting. Patients should be told that AI is a support tool and that final diagnosis depends on qualified clinicians and pathology where needed.

HEALTH-SYSTEM IMPACT AND COST CONSIDERATIONS

The likely benefits of AI in Bangladesh are faster triage, shorter reporting time, improved access to specialist review, more standardized interpretation, and potentially earlier diagnosis. However, these benefits should be demonstrated rather than assumed. Health-system evaluation should include direct costs such as hardware, software, licensing, maintenance, training, cybersecurity, data storage, and staff time. It should also include downstream effects such as biopsy rates, referral volume, treatment initiation, patient travel, and false-positive burden. Cost-effectiveness should be assessed separately for breast and prostate cancer. The breast cancer pathway may show benefit through earlier diagnosis and reduced reporting delay. The prostate pathway may show benefit through improved selection for biopsy and reduced unnecessary procedures. For both pathways, the value proposition depends on safe integration into clinical workflows and measurable patient benefit. An AI tool that improves AUC but does not reduce diagnostic delay, missed cancer, unnecessary biopsy, or cost may have limited policy value.

ETHICAL, LEGAL, AND GOVERNANCE CONSIDERATIONS

AI in cancer diagnosis raises ethical concerns because false-negative outputs can delay treatment and false-positive outputs can cause anxiety, unnecessary biopsy, and cost. In Bangladesh, these risks may disproportionately affect rural and low-income patients if

models are trained mostly on tertiary hospital data. Algorithmic fairness must therefore be assessed by geography, socioeconomic status, age, sex where relevant, imaging device, and referral source when data are available. Data governance should be based on consent or approved waiver, secure storage, limited access, encryption, audit trails, de-identification, and institutional data-sharing agreements. Federated learning should not be presented as automatically privacy preserving; it should be supported by technical safeguards and governance. Any clinical AI system should have a named clinical owner, technical owner, and institutional oversight committee. Liability should be clarified before deployment, especially when AI recommendations are accepted or overridden.

Table 5: Ethical and safety risk mitigation plan

Risk	Possible harm	Mitigation strategy
False-negative classification	Delayed diagnosis and avoidable progression.	High-sensitivity thresholds for triage, mandatory human review of uncertain cases, false-negative audit.
False-positive classification	Unnecessary biopsy, anxiety, cost, and overdiagnosis.	Use AI as decision support, not automatic biopsy trigger; report calibration and PPV.
Dataset bias	Reduced accuracy for rural, poor, younger, or underrepresented patients.	Diverse site inclusion, subgroup reporting, fairness monitoring, recalibration.
Automation bias	Clinicians may accept AI output without sufficient review.	Training, interface warnings, override documentation, periodic audit of human-AI decisions.
Privacy breach	Loss of patient trust and legal harm.	De-identification, access control, encryption, federated learning safeguards, data-use agreements.
Model drift	Performance declines after scanner changes or population shifts.	Continuous monitoring, version control, scheduled recalibration, site-level alerts.

LIMITATIONS AND CONCLUSION

This article proposes a framework and validation roadmap rather than presenting nationally validated clinical performance. The framework depends on assumptions about infrastructure readiness, data availability, institutional collaboration, and regulatory support. Bangladesh currently has limited population-based cancer registry coverage, and many cancer diagnoses occur in fragmented public and private care pathways. Local prostate MRI datasets may be small, and breast imaging data may be concentrated in urban centers. These limitations increase the risk of selection bias and reduce generalizability. The framework should therefore be treated as a starting point for structured implementation, not as evidence that AI should already be deployed at scale.

Another limitation is that AI performance metrics can be misleading when reported without clinical context. High AUC does not guarantee patient benefit. Safe implementation requires prospective testing, human-AI interaction analysis, subgroup evaluation, and post-deployment monitoring. Future research should prioritize pragmatic clinical trials, health-economic analysis, qualitative studies of clinician and patient trust, and national governance models for AI-enabled cancer diagnosis.

Next-generation AI could help improve breast and prostate cancer diagnosis in Bangladesh, but its success will depend on local testing, strong ethics, updated infrastructure, and a focus on people. The updated three-tier framework offers a clear plan: using edge-enabled triage in resource-constrained areas, providing multimodal decision support in larger hospitals, and applying federated learning to improve models nationwide. Together with the author's

previous work on AI-powered oncology diagnostics, predictive analytics, and decentralized clinical decision support, the present framework advances a Bangladesh-specific roadmap for responsible AI implementation in breast and prostate cancer diagnosis. Most importantly, AI should support clinicians as a trusted second reader and workflow tool, not replace them. If Bangladesh builds its own datasets, adheres to international standards, protects patient privacy, and measures real clinical outcomes, with rigorous validation, ethical governance, and continuous monitoring, AI may become a reliable component of Bangladesh's national cancer care and set an example for other low- and middle-income countries.

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