

A Hybridized Mobile Application and Machine Learning System for the Predictive and Diagnostic Screening of Breast and Cervical Cancer with Integrated Herbal Treatment Support: Evidence from Rural Ebonyi State, Nigeria

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Abstract

Cervical and breast cancers remain among the leading causes of cancer-related morbidity and mortality worldwide, with a disproportionate burden in low- and middle-income countries such as Nigeria, where late presentation, weak referral pathways, and limited access to oncological expertise hinder early detection. This study presents a hybridized mobile-application and machine learning system for the predictive and diagnostic screening of breast and cervical cancer, integrated with a structured herbal-treatment knowledge base, developed using Okposi, a rural community in Ebonyi State, Nigeria, as a case study. Four supervised algorithms – Decision Tree, Random Forest, Logistic Regression, and Support Vector Machine (SVM) – were trained and compared on the University of California Irvine breast cancer dataset, while an Extreme Gradient Boosting (XGBoost) classifier was trained on the Hospital Universitario de Caracas cervical cancer dataset. The system, developed in Python with the Flask framework following an Object-Oriented Analysis and Design Methodology (OOADM) for application design and the Cross-Industry Standard Process for Data Mining (CRISP-DM) for the modelling workflow, separates a login-free, rule-based diagnostic module from an authentication-protected machine-learning predictive module. SVM achieved the best breast cancer classification performance (accuracy = 98.2%, precision = 100.0%, recall = 95.3%, F1-score = 97.6%), while XGBoost achieved 93% accuracy and a 96% F1-score for cervical cancer despite marked class imbalance. Unit, integration, and performance testing confirmed that the system performed according to specification. The results demonstrate that a hybridized mobile-machine learning-herbal framework can deliver accessible, low-cost, and culturally relevant early-warning cancer support to underserved communities, offering a template for similar interventions across sub-Saharan Africa.

Keywords: Breast cancer; Cervical cancer; Machine learning; Mobile health; Herbal treatment; Support Vector Machine; XGBoost

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I. Introduction

Oncology, the branch of medicine concerned with the diagnosis and treatment of cancer, continues to confront one of the most pressing global health challenges of the present era. According to the World Health Organization (2025), the incidence of cancer is rising steadily, with tens of millions of new cases diagnosed annually and more than half of affected patients eventually succumbing to the disease; in many countries, cancer ranks as the second leading cause of death after cardiovascular disease (Deo *et al.*, 2022). Data compiled from the International Agency for Research on Cancer and the Global Burden of Disease Cancer Collaboration indicate that cancer cases increased by 28% between 2006 and 2026, with an estimated 2.7 million new cases projected in Nigeria by 2030 (National Cancer Registry, 2022). Among malignancies of particular public-health concern, cancers of the breast and cervix remain leading causes of morbidity and mortality among women worldwide, disproportionately affecting low- and middle-income countries where more than half of cases are detected only at advanced, difficult-to-treat stages (Kavousi *et al.*, 2024; Rakhmanovna and Ugli, 2021).

In Nigeria, and particularly in rural communities, the burden of breast and cervical cancer is compounded by irregular medical check-ups, inadequate healthcare infrastructure, a shortage of oncological specialists, and insufficient health information (Ayón, 2018; Mbunge *et al.*, 2021; Phad *et al.*, 2021). Mobile health (mHealth) technologies have been advanced as a practical means of narrowing this gap, offering accessible platforms for health awareness, self-monitoring, and remote service delivery at comparatively low cost (Mbunge *et al.*, 2021; Nedungadi *et al.*, 2018; Tizifa *et al.*, 2021). Several studies illustrate this promise: Chowdhury *et al.* (2021)

proposed an artificial-intelligence-driven smartphone application for cancer-risk prediction in low-income settings; Tizifa *et al.* (2021) used smartphone applications to improve data quality at rural Malawian health facilities; and Kilua *et al.* (2022) applied mobile technology to track maternal vaccination records. None of these interventions, however, was designed specifically for the combined predictive and diagnostic screening of breast and cervical cancer among rural dwellers, nor did any incorporate the herbal-treatment practices that remain culturally embedded in many Nigerian communities as a result of local religious and behavioural peculiarities.

Artificial intelligence and machine learning have shown considerable promise in cancer research, supporting the optimisation of clinical practice, the prediction of disease outcomes, and improved understanding of tumour biology (Farina *et al.*, 2022). Yet a review of artificial-intelligence applications in African cancer care found that, despite notable innovations such as PapsAI and MinoHealth, algorithmic bias and the absence of herbal-treatment integration remain persistent gaps (Akingbola *et al.*, 2024). Similarly, mHealth implementations for cancer diagnosis in sub-Saharan Africa are frequently constrained by a narrow disease scope, small parameter sets, or weak integration with local referral and treatment pathways (Arendse *et al.*, 2025; Nedungadi *et al.*, 2018). This study addresses these gaps by developing a hybridized mobile-application and machine learning predictive and diagnostic system for breast and cervical cancer, with an integrated herbal-treatment module, using Okposi, a rural community in Ohaozara Local Government Area of Ebonyi State, Nigeria, as a case study.

1.1 Problem Statement

Rural dwellers in Nigeria face compounding health challenges that delay the detection and management of breast and cervical cancer. These include limited access to early diagnostic tools, resulting in late detection and poor patient outcomes; a scarcity of oncological specialists, which raises the cost and duration of care; inadequate or distant medical facilities and personnel, which delay treatment; and limited awareness of herbal supplements that could complement conventional cancer care. These challenges motivate the design of an integrated mobile-based system capable of prediction, diagnosis, and herbal-treatment guidance within a single, accessible platform.

1.2 Aim and Objectives

The study aimed to design and implement a hybridized mobile application and machine learning predictive and diagnostic system for breast and cervical cancer, incorporating herbal-treatment support, to improve healthcare service delivery in rural Nigeria. The specific objectives were to: (i) train and compare machine learning models for the early prediction of breast and cervical cancer and select the best-performing algorithm(s) for deployment; (ii) develop a symptom-based diagnostic module for the early detection of breast and cervical cancer; (iii) integrate a structured database of herbal treatments associated with the management of breast and cervical cancer symptoms; and (iv) evaluate the performance of the resulting hybridized system.

1.3 Scope of the Study

The study focused on the design of an Android-based mobile application combining predictive, diagnostic, and herbal-treatment modules for breast and cervical cancer, using rural communities in Ebonyi State, Nigeria – specifically Okposi, in Ohaozara Local Government Area – as the case-study context.

II. Materials and Methods

2.1 Study Area and System Analysis

Okposi is a predominantly rural community in Ohaozara Local Government Area, Ebonyi State, south-eastern Nigeria. Like many rural communities across the state, Okposi experiences constrained healthcare infrastructure, a shortage of trained medical personnel, and limited access to current health information, all of which impede preventive care, early disease detection, and timely referral. Preliminary system analysis, informed by document review, field observation, and interviews with healthcare workers and community stakeholders, showed that the existing care pathway for a symptomatic patient typically involves an initial visit to a local health centre or chemist, symptomatic treatment with analgesics, repeated visits if symptoms persist, and referral to a township hospital – frequently only after the disease has progressed to an advanced stage. This analysis identified inadequate diagnostic tooling, sparse specialist coverage, high indirect costs of travel and consultation, and limited awareness of complementary herbal options as the principal weaknesses to be addressed by the proposed system.

2.2 Data Acquisition

Two secondary datasets were used to train the predictive models. The breast cancer dataset was obtained from the University of California, Irvine (UCI) Machine Learning Repository (Breast Cancer Wisconsin Diagnostic dataset), comprising 569 patient records described by digitised measurements of cell nuclei from fine-needle aspirate biopsies, of which 357 were labelled benign and 212 malignant. The cervical cancer dataset was obtained from Hospital Universitario de Caracas, Caracas, Venezuela, comprising demographic, behavioural, and historic medical records for 858 patients.

2.3 Data Preprocessing

For the breast cancer dataset, preprocessing involved removal of a redundant index column and an empty unnamed column, encoding of the categorical diagnosis label (benign = 0, malignant = 1), and correlation-based feature selection using the Pandas and Seaborn libraries. Features exhibiting strong positive correlation with malignancy – including worst concave points, worst perimeter, mean radius, and worst area – were retained as the principal predictors, while weakly correlated features (e.g., mean fractal dimension, texture and smoothness standard errors, and symmetry standard error) were dropped. For the cervical cancer dataset, two sparsely populated fields (time since first and time since last sexually transmitted disease diagnosis) were dropped owing to substantial missingness; remaining object-typed fields were converted to numeric type, missing values were imputed using column means, and the dependent variable (cancer diagnosis) was separated from the independent variables prior to model training.

2.4 Model Development

Model development followed the Cross-Industry Standard Process for Data Mining (CRISP-DM) (Wirth and Hipp, 2000), comprising data understanding, preparation, modelling, evaluation, and deployment phases, implemented in Python within the Google Colaboratory environment using Pandas, Scikit-learn, and Joblib. Both datasets were partitioned in a 70:20:10 ratio for training, validation, and testing. For breast cancer classification, four supervised algorithms – Decision Tree, Random Forest, Logistic Regression, and Support Vector Machine – were trained, validated, and compared. For cervical cancer classification, an Extreme Gradient Boosting (XGBoost) classifier was trained on account of its established robustness to moderate class imbalance (Yudha and Rahardi, 2025). Model performance was evaluated using accuracy, precision, recall, and F1-score derived from the confusion matrix, with particular emphasis on recall, reflecting the clinical priority of minimising missed malignancies relative to false positives. The best-performing model for each cancer type was persisted using Joblib for deployment.

2.5 System Design and Architecture

The application architecture was developed using an Object-Oriented Analysis and Design Methodology (OOADM) (Dennis *et al.*, 2015), comprising logical design (system inputs, outputs, and data flow), architectural design (structural and behavioural views), and physical design (data validation, storage, and security) layers. The resulting architecture separates two complementary modules. The diagnostic module is a rule/heuristic-based risk-assessment tool, accessible without user authentication, in which a user selects the cancer type of interest (breast or cervical) and reports observed symptoms; where three or more symptoms – including at least one key symptom – are present, the module flags a suspected case and displays a Low, Medium, or High-risk level. The predictive module is a machine-learning-based tool accessible only after user registration and authentication, in which clinical data are uploaded as a CSV file for inference; the module returns a Benign or Malignant classification together with a confidence score. This architectural separation was a deliberate design choice, intended to keep routine risk screening freely accessible while restricting access to sensitive clinical data behind authentication. In both modules, a positive or elevated-risk outcome triggers two forms of support: a recommendation drawn from a structured herbal-treatment knowledge base, and, where the indicated risk or stage warrants it, a referral suggestion to the nearest appropriate health facility.

2.6 Herbal Treatment Knowledge Base

A structured repository of herbal remedies commonly used in the management of breast and cervical cancer symptoms in Nigerian and other traditional practice contexts – drawing on locally documented ethnobotanical knowledge as well as the emerging evidence on plant-derived anticancer compounds (Cuevas-Cianca *et al.*, 2023; Wu *et al.*, 2025) – was compiled and integrated into the system. The module returns preparation and usage guidance alongside an explicit statement that herbal recommendations are intended as complementary support and do not substitute for professional medical evaluation and treatment.

2.7 Implementation Environment

The system backend was implemented in Python using the Flask micro-framework, exposing RESTful endpoints for user registration, authentication, symptom-based diagnosis, and model-based prediction, while the front end was implemented as an Android mobile client. Minimum device requirements were a screen aspect ratio of 3:4 or higher, 1 GB RAM, 2 GB of storage, and Android 14 or later, reflecting the study's emphasis on lightweight, offline-capable operation suited to low-end devices common in rural settings.

2.8 System Testing

The system was evaluated through unit/module testing of individual components (home page, menu control, diagnosis/prediction, treatment recommendation, and referral functions), integration testing of the

assembled system using live data, and performance testing of response time and overall system behaviour. Expected outcomes for each functional requirement were compared against observed outcomes to confirm that the system met its design specification (Section 3.3).

III. Results

3.1 Breast Cancer Model Performance

Table 1 summarises the performance of the four algorithms evaluated for breast cancer classification.

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Decision Tree	96.5	100.0	90.7	95.1
Random Forest	96.5	97.6	93.0	95.2
Logistic Regression	97.4	97.6	95.3	96.5
Support Vector Machine	98.2	100.0	95.3	97.6

Table 1: Comparative Performance of Machine Learning Algorithms for Breast Cancer Classification

The Support Vector Machine achieved the highest overall performance, with 98.2% accuracy, 100.0% precision, 95.3% recall, and an F1-score of 97.6%. Its confusion matrix (Figure 1) recorded 71 true negatives, 41 true positives, two false negatives, and zero false positives out of 114 test samples, indicating that the model raised no false alarms while missing only two malignant cases. The Decision Tree also achieved perfect precision (100.0%) but recorded the lowest recall (90.7%) of the four models, missing four malignant cases; cross-validated recall of 91.1% obtained during grid search was consistent with test performance, indicating minimal overfitting. Random Forest attained 96.5% accuracy and was the only model to produce a false positive, slightly reducing its precision to 97.6% relative to the Decision Tree, while benefiting from the variance reduction typically associated with ensemble averaging. Logistic Regression, despite its comparative simplicity, achieved 97.4% accuracy and matched the SVM's recall of 95.3%, trailing SVM by only 0.8 percentage points in F1-score.

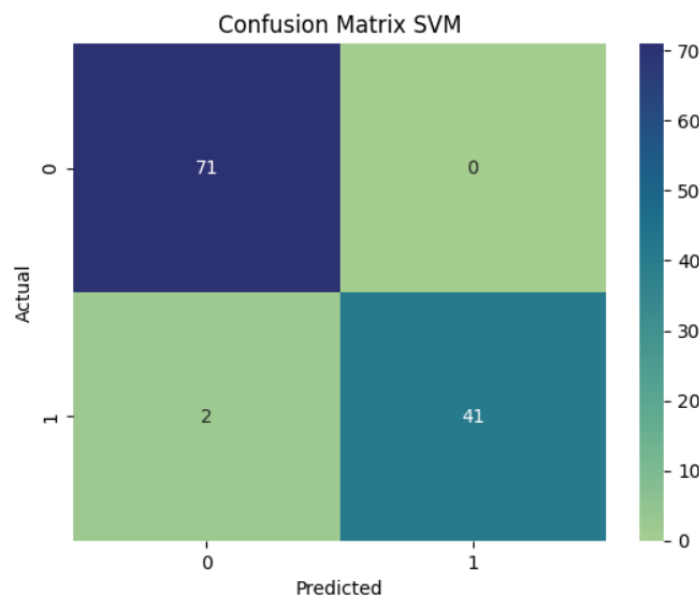


Figure 1: Confusion Matrix of the Support Vector Machine Model for Breast Cancer Classification

3.2 Cervical Cancer Model Performance

For cervical cancer classification, the XGBoost classifier achieved 93% accuracy and an F1-score of 96%. The confusion matrix (Figure 2) shows 192 and 7 correctly classified negative and positive cases respectively, against 12 false positives and 4 false negatives, reflecting the classifier's ability to sustain strong overall classification performance despite the pronounced class imbalance present in the cervical cancer dataset, of which only a small minority of test cases were positive.

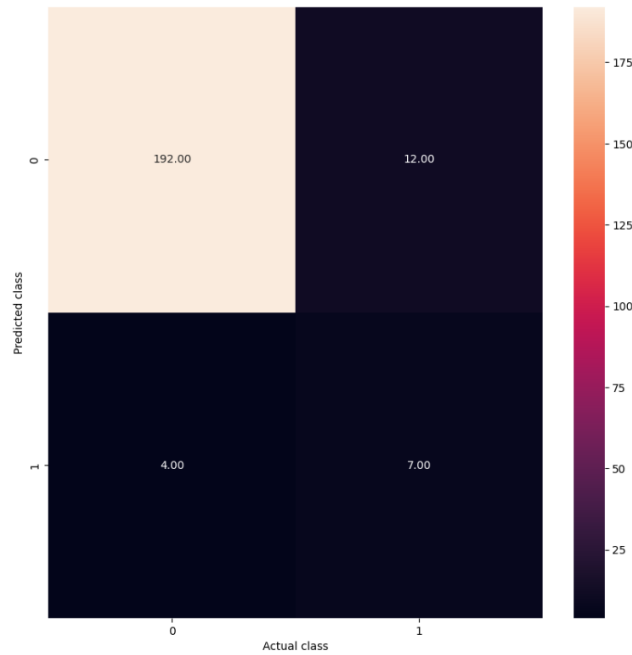


Figure 2: Confusion Matrix of the XGBoost Model for Cervical Cancer Classification

3.3 System Testing Results

Table 2 summarises the outcome of functional system testing conducted in accordance with the plan described in Section 2.8.

Test Conducted	Expected Result	Actual Result
Application launch	Index/module-selection page displays on launch	Module-selection page displayed as expected
Predictive module	System predicts benign/malignant outcome for breast and cervical cancer	Benign/malignant classification returned with confidence score using the trained models
Diagnostic module	System diagnoses breast/cervical cancer risk from selected symptoms	Risk level (Low/Medium/High) returned using the rule-based expert system
Herbal treatment module	System recommends herbal treatment and/or hospital referral	Herbal remedy suggested, with hospital referral where risk/stage warranted

Table 2: Expected versus Actual System Testing Results

In every case, the observed system behaviour matched the expected behaviour. Unit, integration, and performance testing further confirmed that individual modules operated reliably in isolation and in combination, and that system response times were judged satisfactory.

3.4 System Interface

Figure 3 shows the application's home screen, from which users choose between the login-free, symptom-based Diagnostic module and the authentication-protected, machine-learning-based Predictive module, consistent with the architecture described in Section 2.5.

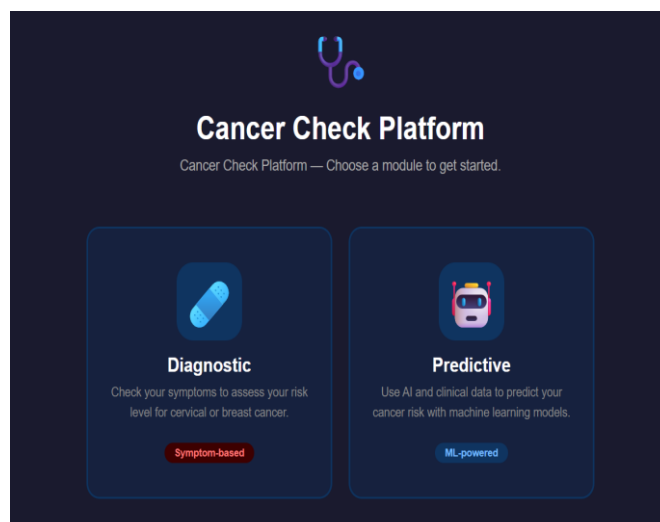


Figure 3: Home Screen of the Hybridized Diagnostic and Predictive Mobile Application

IV. Discussion

The comparative evaluation in Section 3.1 shows that, among the four algorithms tested for breast cancer classification, SVM offered the best balance of precision and recall and is therefore the most clinically defensible choice for deployment: its zero false-positive rate limits unnecessary patient anxiety and avoidable follow-up biopsies, while its high recall limits missed malignancies. The Decision Tree's comparatively low recall illustrates a known limitation of single-tree classifiers, which can over-prune paths to minority-class leaves – here, the malignant class – under aggressive leaf-size constraints, even though correctly identifying that class is the more clinically important task. That Logistic Regression matched SVM's recall despite being the simplest of the four models is a notable finding, suggesting that, in resource-constrained deployments where model interpretability or computational cost is a priority, Logistic Regression may offer an attractive lower-complexity alternative with only a marginal reduction in F1-score. For cervical cancer, XGBoost's robustness to the pronounced class imbalance in the Hospital Universitario de Caracas dataset supports its selection over algorithms more sensitive to skewed class distributions, though the small proportion of positive cases in the test data means that further validation on larger and more balanced datasets remains desirable.

Positioned against prior mHealth interventions, the present system extends the existing literature in several respects. Where Nedungadi *et al.* (2018) developed a personalised monitoring system limited to two physiological parameters, and Tizifa *et al.* (2021) targeted malaria rather than cancer, the present system integrates prediction, symptom-based diagnosis, and herbal-treatment guidance for two distinct cancer types within a single application. Where Chowdhury *et al.* (2021) demonstrated the feasibility of AI-driven cancer-risk prediction on smartphones in low-income settings, the present system extends this approach with a dedicated, rule-based diagnostic pathway and an explicit herbal-treatment recommendation layer. And where Akingbola *et al.* (2024) identified the absence of herbal-treatment integration as a persistent gap in African artificial-intelligence oncology applications, the present system's structured herbal-treatment knowledge base directly addresses that gap while explicitly framing herbal guidance as complementary to, rather than a substitute for, professional medical care. The deliberate architectural separation of an open-access diagnostic module from an authentication-protected predictive module further represents a privacy-conscious design choice not commonly foregrounded in comparable mHealth systems reviewed in this study.

Several limitations should be acknowledged. First, both predictive models were trained on datasets drawn from outside Nigeria (the United States-sourced UCI repository and a Venezuelan hospital), which may limit generalisability to the genetic, environmental, and lifestyle risk profiles of Nigerian women; incorporation of locally collected data through continuous, crowdsourced data-gathering is recommended as future work. Second, the rural deployment context introduces practical constraints – including inconsistent smartphone and internet access, variable digital literacy, and the informal, non-standardised nature of herbal-remedy preparation – that were outside the technical scope of this study but bear directly on real-world adoption and must be addressed through complementary digital-literacy and quality-assurance interventions. Third, the symptom-based diagnostic module is a heuristic screening aid and cannot replace histopathological or clinical diagnosis; its role is confined to flagging risk and prompting referral, consistent with its intended design.

V. Conclusion and Recommendations

This study designed, implemented, and evaluated a hybridized mobile-application and machine learning system for the predictive and diagnostic screening of breast and cervical cancer, integrated with a structured herbal-treatment knowledge base, for deployment among underserved rural communities in Nigeria. Of four algorithms compared for breast cancer classification, SVM achieved the best overall performance (98.2% accuracy, 100.0% precision, 95.3% recall, 97.6% F1-score), while an XGBoost classifier achieved 93% accuracy and a 96% F1-score for cervical cancer classification despite marked class imbalance in the training data. System testing confirmed that the application performed according to its design specification across its predictive, diagnostic, herbal-treatment, and referral functions. Beyond its technical contributions, the study's principal novelty lies in combining machine-learning-based prediction, rule-based diagnostic screening, and herbal-treatment guidance within a single, privacy-conscious, low-end-device-compatible mobile platform – an integration not previously reported for breast and cervical cancer in the Nigerian rural mHealth literature.

Based on these findings, it is recommended that: (i) government and public-health stakeholders explore subsidised, health-optimised mobile devices to improve affordability for low-income rural users; (ii) digital- and health-literacy programmes be developed to support informed adoption of mobile-based screening tools in rural communities; and (iii) future work pursue systematic, crowdsourced collection of Nigerian clinical and demographic data – through partnership with government, health practitioners, and community stakeholders – to enable periodic retraining and localisation of the predictive models, alongside prospective clinical validation studies to assess real-world diagnostic performance and patient outcomes.

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