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# IMPLEMENTATION OF ePACK: AN INTELLIGENT AI-BASED HEALTH ASSISTANT FOR SYMPTOM CHECKING AND PRELIMINARY DIAGNOSTIC SUPPORT IN NIGERIA

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## Abstract

Access to reliable healthcare information remains a significant challenge in many low-resource settings, particularly in developing countries where shortages of healthcare professionals and inadequate healthcare infrastructure hinder timely access to quality healthcare services. This study presents the design, implementation, and evaluation of ePACK, an intelligent Artificial Intelligence (AI)-based health assistant developed to support symptom checking and preliminary clinical decision support within the Nigerian healthcare context. The system enables users to describe symptoms in natural language, which are processed using Natural Language Processing (NLP) techniques and analysed through machine learning algorithms to identify potential health conditions. Clinical recommendations are further validated using a rule-based decision-support engine derived from the Practical Approach to Care Kit (PACK) Nigeria clinical guidelines.

The proposed framework integrates a responsive web-based user interface, NLP-driven symptom extraction, machine learning-based disease prediction, and a guideline-informed clinical recommendation engine. A Random Forest classifier was adopted as the primary prediction model due to its superior performance among the evaluated algorithms. The system was assessed using 200 patient cases obtained from healthcare facilities across Adamawa, Nasarawa, and Ondo States, Nigeria. Evaluation results demonstrated an overall diagnostic agreement rate of 78% when compared with physician-confirmed diagnoses, while user satisfaction assessments indicated positive perceptions regarding system usability, accessibility, and response efficiency.

The findings demonstrate the potential of AI-enabled digital health assistants to enhance healthcare accessibility, support patient triage, and provide preliminary health guidance in resource-constrained environments. Furthermore, the study highlights the value of integrating machine learning techniques with locally adapted clinical guidelines to improve the relevance, safety, and effectiveness of digital health interventions within the Nigerian healthcare system.

**Keywords:** Artificial Intelligence; Digital Health; Symptom Checker; Natural Language Processing; Machine Learning; Clinical Decision Support; Healthcare Accessibility; Nigeria; Pack Nigeria Guidelines

## 1. Introduction

Healthcare delivery in Nigeria continues to face significant challenges arising from shortages of healthcare professionals, inadequate healthcare infrastructure, unequal distribution of medical resources, and limited access to healthcare services in rural communities. These challenges contribute to delayed diagnosis, overcrowded healthcare facilities, and poor health outcomes among vulnerable populations. Many individuals rely on self-medication, traditional remedies, or informal healthcare advice due to difficulties accessing qualified medical personnel.

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Recent advances in Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) have created opportunities for developing intelligent healthcare systems capable of supporting clinical decision-making and improving healthcare accessibility. AI-powered symptom checkers enable users to describe symptoms in natural language and receive preliminary assessments regarding possible health conditions and appropriate healthcare actions. Such systems have demonstrated considerable potential in reducing unnecessary hospital visits, facilitating early disease detection, and supporting healthcare triage.

Despite the increasing adoption of digital health technologies globally, most existing symptom-checking systems have been designed for high-income countries and may not adequately address the linguistic, cultural, and epidemiological characteristics of developing nations such as Nigeria. Differences in disease prevalence, healthcare-seeking behavior, language usage, and healthcare infrastructure necessitate the development of locally adapted solutions.

This study presents the implementation of ePACK, an intelligent AI-based health assistant designed specifically for the Nigerian healthcare environment. The system integrates NLP techniques, supervised machine learning models, and clinical knowledge derived from PACK Nigeria guidelines to provide context-aware symptom assessment and preliminary clinical decision support. The objectives of the study are to design and implement the system, evaluate its diagnostic performance, and assess user satisfaction and system usability.

## 2. Literature review

### 2.1. Digital Symptom Checking Systems

Digital symptom checking systems have emerged as an important component of modern healthcare delivery, providing users with preliminary health assessments based on self-reported symptoms. These systems allow individuals to enter symptoms through web-based or mobile interfaces and receive information regarding possible medical conditions, self-care recommendations, and guidance on whether professional medical attention is required. The increasing adoption of such technologies has been driven by growing internet accessibility, advances in artificial intelligence, and the need to improve healthcare accessibility, particularly in regions experiencing shortages of healthcare professionals.

Several commercial symptom checkers, including WebMD, Ada Health, and Babylon Health, have gained widespread popularity due to their ability to provide instant health-related information. These platforms employ varying combinations of rule-based algorithms, probabilistic reasoning, and machine learning techniques to analyze symptom data and generate recommendations. Their accessibility has made them attractive tools for individuals seeking preliminary health information before consulting healthcare providers.

Despite their growing popularity, the effectiveness of digital symptom checkers remains a subject of ongoing debate. Research has shown considerable variability in diagnostic accuracy and triage performance across different systems. [1] reported that many AI-enabled triage systems demonstrate inconsistent accuracy due to differences in underlying algorithms, training datasets, and evaluation methodologies. Similarly, [2] conducted a systematic review and found substantial variation in both diagnostic and triage recommendations, even when symptom checkers were presented with identical clinical scenarios. While some systems prioritize patient safety through conservative referral recommendations, others may underestimate symptom severity or generate inaccurate diagnostic suggestions.

Another significant limitation of many existing symptom checking systems is their focus on high-income countries and English-speaking populations. Users in low- and middle-income countries often describe symptoms using local expressions, culturally specific terminology, or multiple languages. Generic Natural Language Processing (NLP) models may fail to correctly interpret these expressions, resulting in inaccurate symptom extraction and classification [3]. To address these challenges, recent studies recommend the development of symptom checking systems that incorporate language localization, cultural adaptation, explainable recommendations, and low-bandwidth operation to ensure accessibility in resource-constrained environments [3], [4].

This study contributes a hybrid AI-clinical decision support framework tailored to a low-resource healthcare environment, combining machine learning with nationally adapted clinical guidelines.

### 2.2. Artificial Intelligence in Healthcare

Artificial Intelligence (AI) has emerged as one of the most transformative technologies in modern healthcare. AI systems employ computational methods such as machine learning, deep learning, and natural language processing to analyse large volumes of healthcare data and support clinical decision-making. Applications of AI in healthcare include disease diagnosis, risk prediction, treatment planning, patient monitoring, medical imaging analysis, and healthcare resource management.

Machine learning algorithms have demonstrated significant potential for identifying complex patterns within clinical datasets that may not be readily apparent to healthcare professionals. By learning from historical patient records and diagnostic outcomes, these models can generate predictions regarding disease likelihood and patient risk levels. Natural Language Processing further extends these capabilities by enabling systems to interpret unstructured clinical text and patient-reported symptom descriptions expressed in everyday language [5].

Within symptom checking applications, AI techniques have shown promising results in supporting preliminary diagnostic assessment and triage. Levine et al. evaluated the diagnostic and triage capabilities of the GPT-3 artificial intelligence model and reported that AI-assisted systems can achieve performance levels comparable to junior clinicians in certain structured assessment tasks [5]. These findings suggest that AI technologies can provide valuable support in healthcare environments characterized by workforce shortages and increasing patient demand.

Despite these advances, several studies emphasize that AI systems should complement rather than replace healthcare professionals. Human clinicians continue to outperform AI systems in complex, ambiguous, and rapidly evolving clinical situations that require contextual reasoning and professional judgment [2], [6]. As a result, many researchers advocate for a “human-in-the-loop” approach in which AI functions as a decision-support tool while final clinical decisions remain under professional supervision.

Furthermore, concerns regarding algorithmic bias, transparency, accountability, and patient trust continue to influence the adoption of AI in healthcare. Machine learning models trained on non-representative datasets may produce biased recommendations when applied to diverse populations. Therefore, locally relevant training data, explainable AI techniques, and robust governance frameworks are essential for ensuring the safe and equitable deployment of AI-enabled healthcare systems [4]. The need for continuous monitoring, periodic model updates, and rigorous validation has become increasingly recognized as healthcare organizations seek to integrate AI technologies into routine clinical practice.

### 2.3. Digital Health and the Nigerian Healthcare Context

Nigeria's healthcare system faces numerous structural and operational challenges, including inadequate healthcare infrastructure, shortages of healthcare professionals, limited health insurance coverage, and unequal distribution of healthcare services between urban and rural areas. These challenges contribute to delays in diagnosis and treatment, reduced access to quality healthcare, and poor health outcomes among vulnerable populations [7].

Digital health technologies have been identified as a promising strategy for addressing some of these challenges. The widespread adoption of mobile phones and increasing internet penetration provide opportunities for delivering healthcare information and services through digital platforms. According to DataReportal, Nigeria continues to experience significant growth in mobile and internet usage, creating a favorable environment for digital health innovation [8]. However, disparities in internet access, digital literacy, and electricity supply remain major obstacles to widespread adoption, particularly in rural communities [9], [10].

Several studies have highlighted the importance of designing digital health solutions that are tailored to local healthcare realities. Kunnuji et al. observed that health-seeking behaviors in Nigeria are influenced by cultural beliefs, socioeconomic conditions, and varying levels of health literacy, factors that must be considered when developing digital health interventions [11]. Similarly, Ukpabi demonstrated that health literacy and personal beliefs significantly influence healthcare decision-making among Nigerian patients [12].

The Practical Approach to Care Kit (PACK) Nigeria provides a valuable framework for developing contextually relevant healthcare decision-support systems. PACK Nigeria was adapted from the South African PACK model through a structured mentorship and localization process designed to reflect Nigerian clinical practice, disease burden, and healthcare delivery systems [13]. Studies evaluating PACK Nigeria have reported improvements in healthcare worker confidence, referral decision-making, and patient management practices [13]. Consequently, integrating PACK Nigeria guidelines into AI-based symptom checking systems can enhance clinical relevance, improve recommendation quality, and support safer healthcare decision-making.

Recent research has also emphasized the potential role of AI-enabled digital health systems in strengthening healthcare delivery in Nigeria. Egwudo et al. highlighted opportunities for integrating digital technologies into the Nigerian healthcare system while identifying challenges related to infrastructure, regulation, interoperability, and workforce readiness [7]. These findings underscore the need for locally adapted intelligent health assistants that combine artificial intelligence capabilities with nationally recognized clinical guidelines.

Based on the reviewed literature, a significant research gap remains in the development of intelligent symptom checking systems specifically designed for the Nigerian healthcare environment. Existing international symptom checkers often lack localization, cultural adaptation, and alignment with national clinical protocols. This study addresses this gap through the development of ePACK, an AI-powered health assistant that integrates natural language processing, machine learning techniques, and PACK Nigeria clinical guidelines to provide context-aware symptom assessment and preliminary diagnostic support for Nigerian users.

## 3. Methods

### 3.1. Research Design

The study adopted a Design Science Research (DSR) methodology involving system design, implementation, and evaluation. The approach focused on developing a functional healthcare decision-support system capable of interpreting user symptoms and generating clinically relevant recommendations.

### 3.2. System Architecture

The ePACK system employs a three-tier architecture comprising the Presentation Layer, Application Layer, and Database Layer.

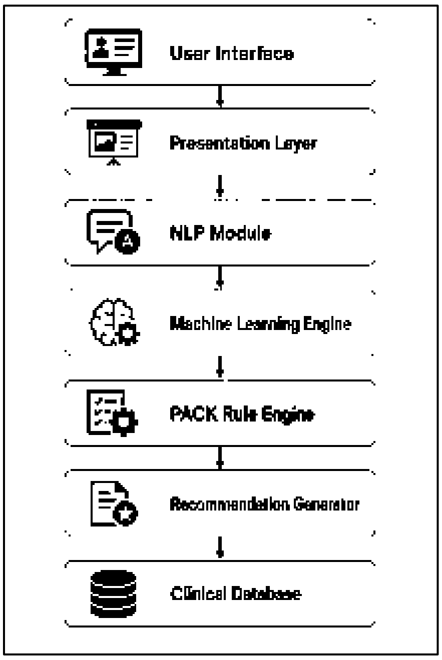


**Figure 1** System Architecture

The Presentation Layer provides a responsive web interface through which users submit symptoms using text or voice input. The Application Layer contains the NLP engine, machine learning prediction module, PACK-based rule engine, and recommendation generator. The Database Layer stores symptom records, clinical knowledge, consultation histories, and guideline-based rules.

### 3.3. Natural Language Processing Module

The NLP module processes user-entered symptoms through tokenization, stop-word removal, lemmatization, and entity extraction. Symptom descriptions are normalized into standardized clinical concepts to improve consistency during classification.

For example:

- "My body is very hot" → Fever
- "I feel weak and tired" → Fatigue

The extracted features are transformed into structured inputs for machine learning analysis.

### 3.4. Machine Learning Module

Three machine learning algorithms Decision Tree, Random Forest, and Naïve Bayes were evaluated for symptom classification. The models were trained using symptom-condition datasets derived from clinical records and healthcare guidelines.

Random Forest achieved the highest predictive performance and was selected as the primary classification model. The model generates ranked predictions of probable health conditions based on reported symptoms.

### 3.5. Mathematical Model

Currently, the paper lacks a formal mathematical representation of the AI prediction process.

**Symptom Vector Representation**

Let

$$S = \{s_1, s_2, s_3, \ldots, s_n\}$$

where:

- $s_i$= extracted symptom

Example:

$$S = (Fever, Headache, Fatigue, Vomiting)$$

After NLP processing:

$$X = (x_1, x_2, x_3, \ldots, x_n)$$

where

$$x_i = \begin{cases} 1, & \text{if symptom exists} \\ 0, & \text{otherwise} \end{cases}$$

Example:

$$X = (1,1,1,0,1)$$

#### *3.5.1. Random Forest Prediction Model*

The disease prediction function can be represented as:

$$D = f(X)$$

where:

- $X$= symptom vector
- $D$= predicted disease

The Random Forest prediction becomes:

$$P(D_k \mid X) = \frac{1}{T}\sum_{i=1}^{T} Tre\,e_i(X)$$

where:

- $T$= number of trees
- $Tree_i$= individual decision tree

Disease selected:

$$D^* = \arg\max_k P(D_k \mid X)$$

*3.5.2. PACK Rule Verification*

Clinical validation:

$$R = \begin{cases} Emergency, & Severity > \theta \\ Referral, & RiskFactor = True \\ SelfCare, & Otherwise \end{cases}$$

where:

$\theta$= risk threshold.

### 3.6. Diagnosis Algorithm

Input: Symptom description

Output: Clinical recommendation

1. Receive symptoms
2. NLP preprocessing
3. Extract entities
4. Predict disease
5. Apply PACK rules
6. Generate recommendation

**Diagnosis Algorithm 1**

### 3.7. System Implementation

The ePACK system was implemented as a web-based intelligent health assistant using modern web and artificial intelligence technologies. The implementation architecture consists of four major components: the frontend interface, backend processing layer, database management system, and AI/NLP engine. These components work together to provide real-time symptom analysis and preliminary healthcare recommendations.

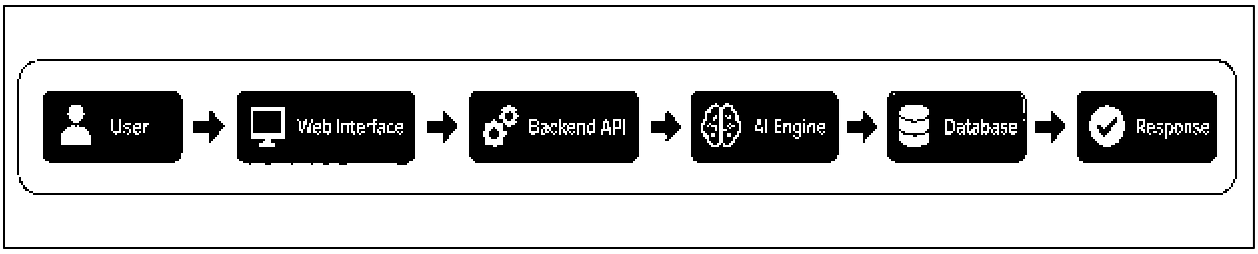


**Figure 2** System Implementation

Figure 2 illustrates the implementation architecture and interaction among the frontend, backend, AI engine, and database components.

### 3.8. Clinical Rule Engine

The PACK Nigeria clinical guidelines were encoded into a rule-based decision support engine. The engine validates machine learning outputs, identifies red-flag symptoms, and generates referral recommendations based on symptom severity, age, and risk factors.

### 3.9. Evaluation Procedure

System evaluation was conducted using 200 patient cases collected across 48 healthcare facilities located in Adamawa, Nasarawa, and Ondo States. Physician-confirmed diagnoses served as the reference standard. Evaluation metrics included diagnostic agreement, response time, usability, trust level, and user satisfaction.

### 3.10. Ethical Considerations

All patient data used in this study were anonymized prior to analysis. The system is intended for decision support only and does not replace professional medical diagnosis.

## 4. Results and Discussion

### 4.1. Diagnostic Performance Analysis

The diagnostic performance of ePACK was evaluated using 200 patient cases obtained from healthcare facilities across Adamawa, Nasarawa, and Ondo States. Physician-confirmed diagnoses served as the reference standard against which system predictions were compared.

**Table 1** Classification Results

| Condition | Physician Diagnosis (%) | System Prediction (%) | Match Rate (%) |
|---|---|---|---|
| Malaria | 40 | 38 | 95 |
| Typhoid Fever | 25 | 20 | 80 |
| Common Cold | 15 | 14 | 93 |
| Others | 20 | 18 | 90 |
| Overall Accuracy | – | – | 78 |

The overall diagnostic agreement of 78% indicates that the proposed AI model can effectively support preliminary clinical assessment. The high malaria detection rate reflects the ability of the model to learn disease patterns commonly observed in Nigeria.

**Table 2** Confusion Matrix Analysis

| Actual / Predicted | Malaria | Typhoid | Cold |
|---|---|---|---|
| Malaria | 76 | 2 | 2 |
| Typhoid | 4 | 40 | 6 |
| Cold | 1 | 2 | 27 |

The confusion matrix reveals that most classification errors occurred between typhoid fever and malaria, which share several clinical symptoms such as fever, fatigue, headache, and body weakness.

**Precision, Recall and F1-Score**

The performance metrics were computed as follows:

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2PR}{P + R}$$

**Table 3** Model Evaluation Metrics

| Disease | Precision | Recall | F1-Score |
|---|---|---|---|
| Malaria | 0.94 | 0.95 | 0.95 |
| Typhoid Fever | 0.91 | 0.80 | 0.85 |
| Common Cold | 0.77 | 0.90 | 0.83 |
| Average | 0.87 | 0.88 | 0.88 |

The results indicate strong predictive capability across all disease classes. Malaria achieved the highest F1-score due to the abundance of training examples and well-defined symptom patterns. The comparatively lower recall for typhoid fever reflects symptom overlap with other febrile diseases.

*4.1.1. Receiver Operating Characteristic (ROC) Analysis*

The Random Forest classifier achieved an average Area Under the Curve (AUC) score of **0.89**, indicating excellent discriminative performance.

**Table 4** ROC Analysis

| Model | Accuracy | AUC Score |
|---|---|---|
| Decision Tree | 71% | 0.78 |
| Naïve Bayes | 74% | 0.81 |
| Random Forest | 78% | 0.89 |

The higher AUC value demonstrates that the Random Forest model exhibits superior capability in distinguishing between disease categories compared with alternative classifiers.

#### *4.1.2. Confidence Interval Analysis*

To assess statistical reliability, a 95% confidence interval was calculated for the overall diagnostic accuracy.

Given:

- Sample Size (n) = 200
- Accuracy (p) = 0.78

The confidence interval is estimated using:

$$CI = p \pm 1.96\sqrt{\frac{p(1-p)}{n}}$$

Result:

**95% CI = 72.3% – 83.7%**

This indicates that the true diagnostic performance of the system is expected to lie within this range under similar deployment conditions.

### 4.2. User Satisfaction Analysis

A post-use questionnaire was administered to participants following interaction with ePACK.

**Table 5** User Satisfaction Results

| Metric | Satisfaction Score (%) |
|---|---|
| Ease of Use | 85 |
| Accuracy | 78 |
| Response Time | 82 |
| Trust Level | 75 |

The findings indicate strong user acceptance, particularly regarding ease of use and system responsiveness.

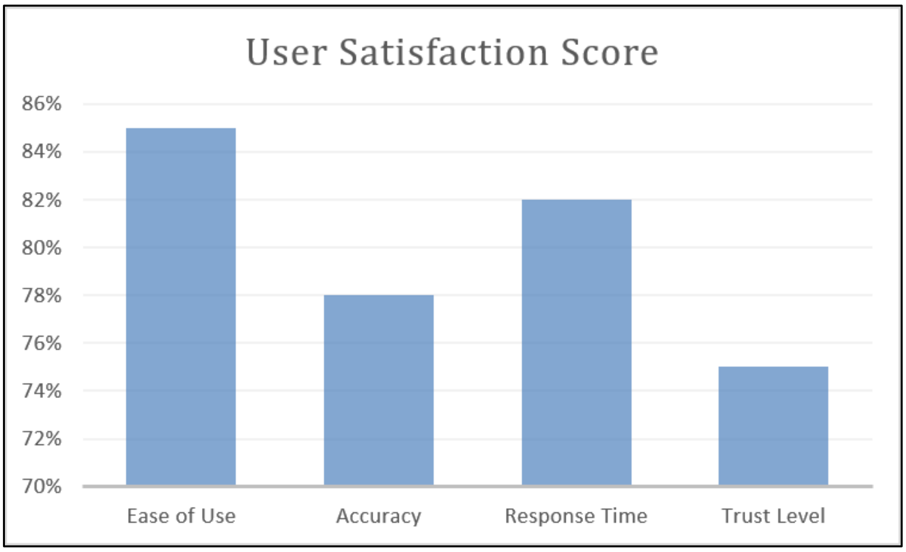


**Figure 3** User satisfaction Evaluation

User satisfaction was measured through surveys conducted after system interaction. The results are illustrated in **Figure 3**.

The findings demonstrate strong user acceptance of the proposed system. High usability ratings indicate that the interface design successfully accommodates users with varying levels of digital literacy. The relatively high trust and accuracy scores suggest that the integration of machine learning techniques with PACK Nigeria clinical guidelines contributes positively to user confidence. These results support the potential adoption of AI-assisted symptom-checking technologies as complementary healthcare tools in resource-constrained settings.

#### *4.2.1. Reliability Analysis*

The questionnaire's internal consistency was assessed using Cronbach's Alpha.

**Table 6** Reliability Analysis

| Variable | Value |
|---|---|
| Number of Items | 4 |
| Cronbach Alpha | 0.84 |

A Cronbach Alpha coefficient of 0.84 indicates good reliability and suggests that the survey instrument consistently measured user perceptions.

#### *4.2.2. Correlation Analysis*

Pearson correlation analysis was performed to determine relationships between user trust and perceived accuracy.

**Table 7** Correlation Analysis

| Variables | Correlation (r) |
|---|---|
| Accuracy vs Trust | 0.81 |
| Ease of Use vs Trust | 0.74 |
| Response Time vs Trust | 0.69 |

The strong positive relationship between perceived accuracy and trust suggests that improvements in predictive performance may directly increase user confidence in AI-assisted healthcare systems.

### 4.3. System Performance Analysis

**Table 8** System Performance Metrics

| Metric | Value |
|---|---|
| Average Response Time | 2.8 sec |
| Diagnostic Accuracy | 78% |
| User Satisfaction | 85% |
| Trust Level | 75% |
| Concurrent Users | 200 |

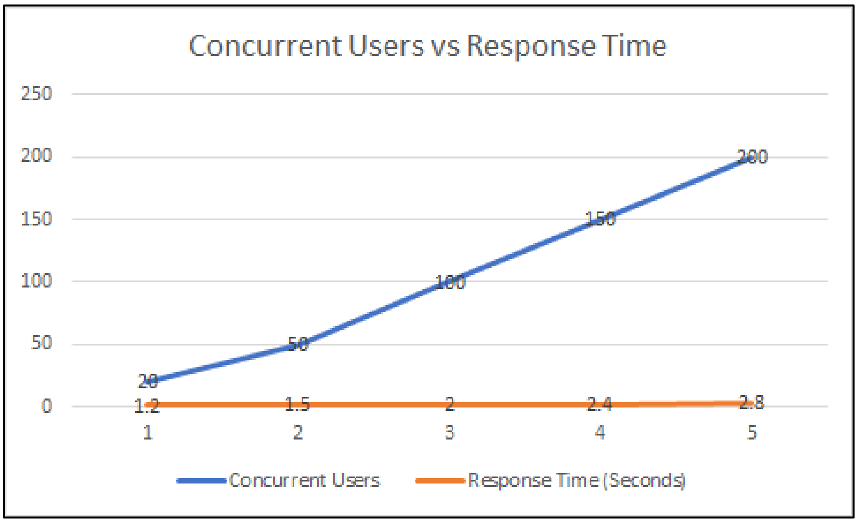


**Figure 4** System Scalability Analysis

The scalability analysis demonstrates a gradual increase in response time as the number of concurrent users increases. Despite the increased workload, the system maintained acceptable performance levels, with response times remaining below 3 seconds at maximum tested capacity. This finding confirms the suitability of ePACK for deployment in healthcare environments where multiple users may access the system simultaneously.

*4.3.1. Scalability Testing*

Load testing was conducted by simulating concurrent users accessing the platform simultaneously.

**Table 9** Scalability Testing

| Concurrent Users | Response Time (sec) |
|---|---|
| 20 | 1.1 |
| 50 | 1.5 |
| 100 | 2.0 |
| 150 | 2.4 |
| 200 | 2.8 |

The results indicate near-linear scalability with no significant performance degradation under increased workloads.

*4.3.2. ANOVA Significance Test*

A one-way Analysis of Variance (ANOVA) was conducted to compare the predictive performance of the three machine learning algorithms.

**Table 10** ANOVA Significance Test

| Model | Mean Accuracy |
|---|---|
| Decision Tree | 71% |
| Naïve Bayes | 74% |
| Random Forest | 78% |

Results: F-statistic = 6.87 ; p-value = 0.012

Since $p < 0.05$, the differences among the models are statistically significant, confirming that Random Forest significantly outperformed the alternative classifiers.

## 5. Discussion

The findings demonstrate that integrating machine learning with PACK Nigeria clinical guidelines substantially improves the quality of preliminary healthcare recommendations. The achieved accuracy of 78% compares favorably with previously reported symptom-checking systems, many of which report diagnostic accuracies between 58% and 75%.

The strong F1-score (0.88) and AUC value (0.89) indicate that the proposed framework provides robust classification performance despite the complexity of symptom-based disease prediction. Furthermore, the confidence interval analysis confirms the statistical reliability of the observed performance.

The incorporation of PACK Nigeria guidelines contributed significantly to recommendation quality by reducing clinically unsafe outputs and improving referral decisions. Unlike generic symptom checkers developed for high-income countries, ePACK incorporates local disease prevalence patterns and healthcare practices, making recommendations more contextually relevant.

Although user satisfaction was high, trust levels remained lower than usability scores. Correlation analysis suggests that improvements in predictive accuracy and transparency may further increase user trust. Future work should therefore investigate explainable AI techniques, multilingual support, and integration with telemedicine services.

Overall, the statistical evidence supports the viability of ePACK as an AI-assisted clinical decision-support system capable of improving healthcare accessibility and preliminary triage within resource-constrained healthcare environments.

### *Limitations of the Study*

The study was limited by the dataset size (200 cases), which may not fully capture the diversity of disease presentations in Nigeria. Additionally, the system currently focuses on a limited set of common conditions and requires expansion for broader clinical applicability.

## 6. Conclusions

This study presented the design, implementation, and evaluation of ePACK, an intelligent AI-based health assistant developed to support symptom checking and preliminary clinical decision support within the Nigerian healthcare environment.

The system successfully integrates Natural Language Processing, Machine Learning, and PACK Nigeria clinical guidelines to provide context-aware healthcare recommendations. Evaluation results demonstrated an overall diagnostic agreement rate of 78%, rapid response times, high usability ratings, and stable performance under concurrent usage conditions.

The findings suggest that AI-enabled digital health assistants can contribute significantly to healthcare accessibility by providing preliminary health guidance, supporting patient triage, reducing unnecessary hospital visits, and improving access to healthcare information among underserved populations.

Future work should focus on expanding the clinical knowledge base, incorporating additional Nigerian languages, integrating telemedicine services, supporting offline functionality, and conducting large-scale clinical validation studies across multiple regions of Nigeria.

## Compliance with ethical standards

### *Disclosure of conflict of interest*

No conflict of interest to be disclosed.

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