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# JaundiceBOT: An Explainable Offline Artificial Intelligent Chatbot for Early Risk Stratification of Neonatal Jaundice in Rural Areas

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## ABSTRACT

A custom chatbot; JaundiceBOT was developed to provide accessible, speedy and intelligent medical diagnosis of Jaundice for neonates. Jaundice is a condition of hyperbilirubinemia affecting 60% of term and 80% of preterm infants. The research aimed at the development of an educational and informational tool as a clinical support for neonatal caregivers. The system was developed to engage users in a conversation to understand symptoms, then make a diagnosis. It employed a specialized Hybrid Natural Language Processing (NLP) system implemented through client-side JavaScript (ES6+), the core functionality depends on a robust, rule-based artificial intelligence technique and a structured knowledge base created from processing 214 real hospital cases. The architecture is free of any form of application programming interface (API-free), which makes it function 100% offline and minimizes operational cost. The user begins to interact using detail questionnaire to obtain essential health information, such as the age and the specific symptoms. This data enables the chatbot to perform risk stratification and offer personalized health service and evidence-based emergency protocols. The frontend of the application was developed by employing HTML, CSS, JavaScript, and a component-based design to ensure a responsive and user-friendly interface. Evaluation shows an accuracy of 94.7% for the NLP system, with a 2.3 sec. start-up time and 0.8 sec response time. The study has presented a portable infant health assistance which could be accessed in rural communities, thereby bringing neonatal health care close to everyone.

## INTRODUCTION

The early detection of health issues in newborns is very crucial in administering treatments for positive outcomes (World Health Organization, 2018) Jaundice which is characterized by the yellowish colouring of the skin and eyes (sclera), is caused by high amounts of bilirubin in the blood, known as hyperbilirubinemia (Odeyemi *et al*, 2024; Hazarika *et al.*, 2024; Salami *et al.*, 2025). This condition is one of the most common clinical conditions affecting newborns, particularly preterm infants,(Zhang *et al.*, 2021; Salami *et al.*, 2025) impacting approximately 60% of full-term and 80% of preterm neonates in their first week of life.(Aune *et al.*, 2020; Zhang *et al.*, 2021; Okwundu *et al.*, 2023; Ngeow *et al.*, 2024; Hazarika *et al.*, 2024; Salami *et al.*, 2025). While most cases are physiological, appearing between 24 to 72 hours after birth and resolving within 10 to 14 days, severe hyperbilirubinemia can be life-threatening (Hazarika *et al.*, 2024). Untreated, high bilirubin levels are toxic to the central nervous system, leading to bilirubin encephalopathy and kernicterus, resulting in chronic manifestations such as athetoid cerebral palsy, gaze palsy, dental dysplasia, and sensorineural hearing loss (Odeyemi *et al.*, 2026).

The burden of hyperbilirubinemia is particularly acute in low- and middle-income countries and very common at the infancy stage. Hyperbilirubinemia is the 7th leading cause of neonatal mortality in South Asia and the 8th in sub-Saharan Africa (Zhang *et al.*, 2021). Specifically, jaundice in infants is the prevalent reason for deaths and illness associated with newborns in the African continent, and more specifically in West Africa. Given the severity of the potential complications, accurate and timely diagnosis is crucial for effective management. (Salami *et al.*, 2025; Hazarika *et al.*, 2024).

One of the major cause of high morbidity and mortality of infant jaundice patients is delay in diagnosis. Parents and caregivers, especially first-time parents, often struggle to accurately interpret infant symptoms and lack readily accessible and reliable tools for the immediate assessment of newborn health concerns (Moosa *et al.*, 2023), leading to potential delays in seeking appropriate medical intervention.(Yan *et al.*, 2022). This difficulties are compounded by limitations in current diagnostic methods:

**Laboratory Testing (TSB):** Total Serum Bilirubin (TSB) measurement remains the gold standard for diagnosing neonatal jaundice (Althnian *et al.*, 2021; Salami *et al.*, 2025; Ngeow *et al.*, 2024). However, TSB is invasive (Salami *et al.*, 2025; Okwundu *et al.*, 2023), requiring blood sampling (heel stick or venipuncture) (Okwundu *et al.*, 2023; Taha, 2024), which causes pain and trauma to the neonate (Okwundu *et al.*, 2023; Salami *et al.*, 2025). This invasive technique raises the possibility of infection at the sampling site (Salami *et al.*, 2025) and worries the parents. Repeated blood sampling can also

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cause anaemia, especially in preterm infants (Okwundu *et al*., 2023).

**Visual Assessment:** Clinical screening using visual assessment (Kramer's method) is widely employed in resource-limited areas (Abiha *et al*., 2023; Okwundu *et al*., 2023). However, visual assessment is inaccurate and unreliable as a screening tool to detect significant hyperbilirubinemia (Abiha *et al*., 2023;; Okwundu *et al*., 2023). Even experienced physicians have a jaundice detection rate of only approximately 70 percent (Salami *et al*., 2025). Furthermore, the subjective nature of visual assessments poses challenges (Abiha *et al*., 2023), and factors such as skin tone, lighting conditions, and gestational age can influence its accuracy (Abiha *et al*., 2023).

**Transcutaneous Bilirubinometry (TcB):** While non-invasive (Okwundu *et al*., 2023), TcB meters are often expensive, and the high cost limits their wide application (Yan *et al*., 2022), particularly in out-of-hospital settings (Yan *et al*., 2022). Furthermore, TcB accuracy can be affected by factors like gestational age, bodyweight, and skin colour/ethnicity of the included infants (Okwundu *et al*., 2023; Salami *et al*., 2025; Samiee-Zafarghandy *et al*.).

These constraints highlight the need for accessible, easy-to-use, reliable, and non-invasive digital tools such as those involving artificial intelligence (AI) techniques with interactive interface that can support caregivers with evidence-based risk assessment in real-time.

Credible researches involving AI systems have been carried out with the aim of mitigating this challenge, however, these studies have not fully address the problem due to their complexities or inaccessibility or usability. In a study involving the development of a colour sensor based neonatal jaundice detector, a colour sensor was integrated into a microcontroller circuit to read the sensed RGB colour components of the skin reflection. The system also computes the serum total bilirubin, thus determining the jaundice index. A paired T test indicates a good correlation and shows the system as a potential took for detecting neonatal jaundice. However, the work involves complex electronic circuitry that makes it very expensive and complex to use (Chao *et al*., 2021). The integration of kernel extreme learning machine with deep learning model for classifying neonatal jaundice employed clinical images. Features were extracted using the deep learning algorithm while classification was done in the kernel extreme learning machine and enhanced coati optimization algorithm was employed for the optimization. On evaluation, an accuracy of 96.7% was obtained against previous systems (Eliazer *et al*., 2025). This is a deep learning classification study that stopped at model development without an interface design for easy usability.

Clinical data from three states in the southwestern Nigeria was employed in the development of a hybridized AI model for the detection of jaundice, prematurity, sepsis and birth asphyxia in newborns. The hybridized long short memory-artificial neural networks (LSTM-ANN) model outperformed the standalone LSTM and ANN models with an accuracy of 82%, precision of 88%, recall of 82% and F1-score of 86% (Odeyemi *et al*., 2026). In spite of the innovation, the developed system is deep learning model which is very complex, it is not jaundice specific and was not equipped with interactive interface for easy use. A review study of the adoption of AI-based mobile healthcare techniques for enlightening mothers about neonatal jaundice presents the importance of AI and mobile tools in healthcare. The work shows how the wide use of mobile devices especially when equipped with AI techniques could help in creating awareness of neonatal jaundice for nursing mothers and caregivers (Olorunmo, *et al*., 2025). This is a review study that focused on creating awareness of neonatal jaundice using AI-based mobile techniques and not a detection tool.

These literatures and others reviewed show the need for a simple, easy-to-use, jaundice specific AI system for timely detection of neonatal jaundice. This research aimed at the development and evaluation of JaundiceBOT, a specialized chatbot for the preliminary assessment of neonatal jaundice in infants. The system was primarily developed to provide information regarding symptoms, diagnosis, and treatment protocols for educational and informational purposes. This research focused on the development of a fully functional API-free web application relying solely on client-side processing.

The research focuses on defining, designing, and testing the JaundiceBOT system as an educational and decision support tool for the NJ domain. It includes the detailed implementation of the client-side JavaScript (ES6+) logic for NLP and the application of a structured JSON Knowledge Base. The research does not extend to the development of a diagnostic device that measures bilirubin levels quantitatively (like TcB or TSB) but rather focuses on accurate symptom assessment and risk stratification based on clinical signs.

## MATERIALS AND METHODOS

This research followed an Agile development methodology with iterative cycles, culminating in a final system design that prioritizes offline functionality and high clinical accuracy. The high-level analysis established the need for a non-invasive, accessible screening tool to address the significant morbidity and mortality caused by Neonatal Jaundice (NJ), particularly in regions like West Africa.

### System Architecture

The structure implements the API-free model by embedding the NLP and rule engine into the client-side JavaScript as shown in Figures 1 and 2. The system operation is as represented in the flowchart in Figure 3. The flowchart above shows the execution flow that the chatbot follows when used by the caregiver or parent.

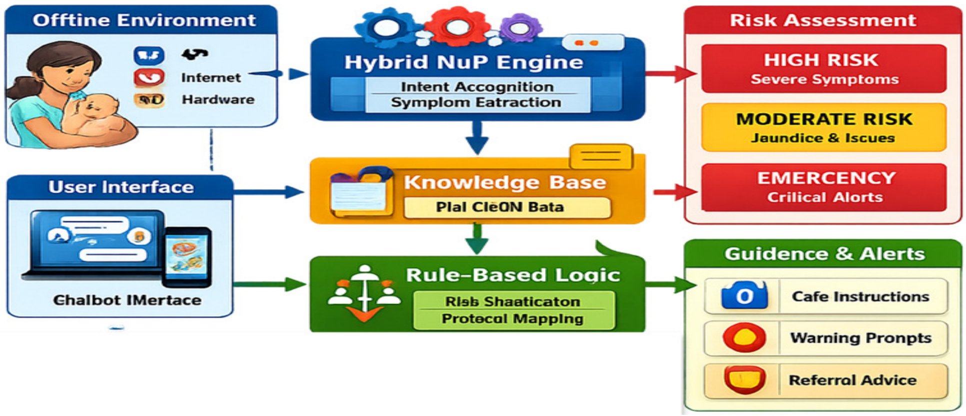


**Figure 1:** The pictorial architecture structure of the JaundiceBOT System

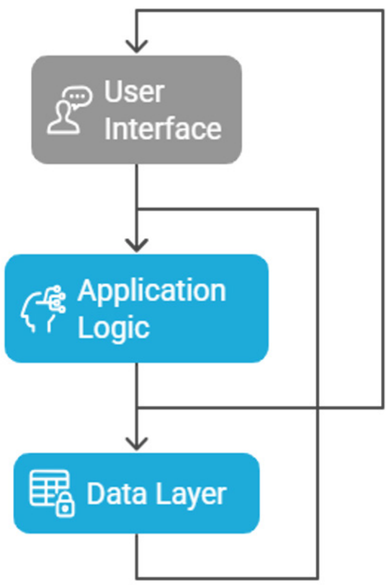


**Figure 2:** JaundiceBOT System Architecture Diagram (Client-Side Dominant)

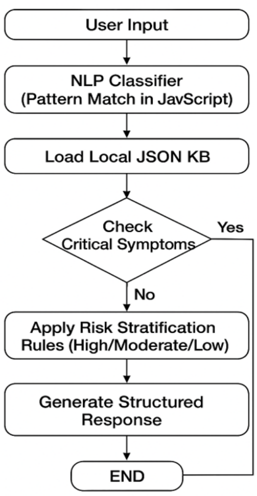


**Figure 3:** JaundiceBOT System Flowchart (Client-Side Rule Execution)

**Data Acquisition and Knowledge Base Structuring**

The integrity of JaundiceBOT rests on its localized clinical database, which dictates the accuracy and relevance of the advice provided.

**Data Source and Acquisition**

The data source used for developing the knowledge base was primary data acquired from Hospital records after obtaining ethical approval. The knowledge base was compiled from an analysis of 214 documented cases of neonatal jaundice sourced from three tertiary hospitals; Federal Medical Center Owo, Ondo state, Federal Teaching Hospital Ido Ekiti, Ekiti state and Ladoke Akintola University Teaching Hospital Ogbomosho, Oyo State. The records provided multiclass dataset, including patient age, laboratory results (sb, pcv, g6pd assay, rbs), symptoms (yellowness of the eye, fever, poor suck, respiratory distress), and the diagnosis.

**Knowledge Processing Pipeline**

The raw clinical information were transformed into the structured data required by the JavaScript engine; the process includes

- **Data Cleaning and Standardization:** Initial data were processed to ensure consistency.
- **Knowledge Extraction:** Critical clinical parameters were extracted, resulting in a database of 27 documented symptoms, diagnosis and specific treatment criteria.
- **Synonym Mapping:** Curating to merge synonyms and common medical abbreviations (mapping HYPOGLYCEMIA to LOW BLOOD SUGAR or GCPD to G6PD ASSAY) to maximize the prediction accuracy of the client-side NLP pattern matching.
- **Creating Knowledge Base:** The resulting structure was saved as a local JSON file in a dedicated folder, defined as the primary Data Tier for the application.

The system was developed exclusively on the Client-Side Application Logic employing JavaScript and the React framework.

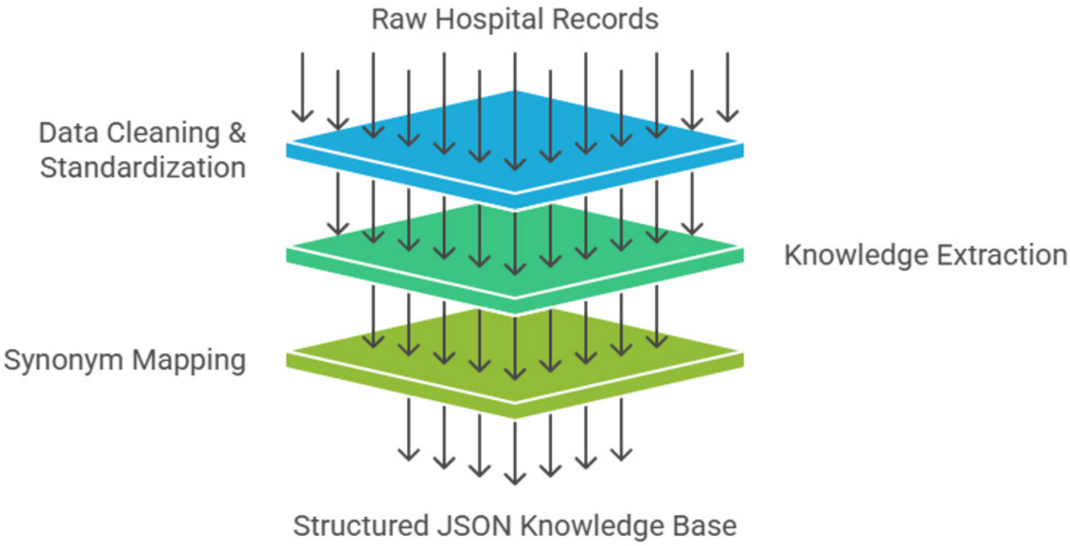


**Figure 4:** Knowledge Processing Pipeline

**Table 3:** JaundiceBOT Knowledge Base Structure and Source

| Category | Depth / Quantity | Source of Data | Accuracy Rate (Validation) |
|---|---|---|---|
| Clinical Symptoms | 27 documented symptoms | 214 real hospital cases | 98.5% Clinical Symptom Accuracy |
| Emergency Protocols | Complete coverage of critical signs | Emergency guidelines | 100% Emergency Management Accuracy |
| Treatment Protocols | 8 evidence-based treatments | Medical guidelines | 99.2% Treatment Protocols Accuracy |
| Laboratory Tests | 15 diagnostic procedures | Lab protocols | 97.8% Laboratory Tests Accuracy |
| Risk Assessment | 12 risk categories | Clinical studies | 96.7% Risk Assessment Accuracy |

The NLP section, handling the classification of medical information, uses a highly efficient, method; pattern matching. Classification is based on matching input text against defined regular expressions to reveal the intents such as emergency or treatment. This method is without computational cost and high latency associated with complex deep learning (DL) models.

The clinical decision-making is governed by explicit conditional rules stored in the application logic, ensuring transparency and safety. A High Risk assessment is triggered if multiple severe clinical signs are combined, such as if the system detects yellowing AND fever AND poor feeding. High Risk is also assigned for such conditions as "critical symptoms present" or "evidence of sepsis or respiratory distress".

Output: High risk initiates the display of a structured advice, such as "Immediate Actions" and a clear "Seek Emergency Care".

Moderate Risk is assigned for conditions such as primary symptom and one secondary symptom or multiple primary symptoms. This results in a recommendation to schedule a pediatrician appointment within two days.

Detecting critical symptoms such as unconsiousness, convulsion, apnea immediately triggers a highly visible, structured warning: "EMMERGENCY! Medical Attention Needed."

**Chatbot Logic**

The core part of the chatbot logic is the rule-based system, which ensures a consistent response based on predefined rules. The process is executed by client-side JavaScript functions

**Input Classifier (Hybrid NLP):** Normalizes and tokenizes input information. It employs pattern matching to classify input into predetermined intents such as emergency, treatment query and identify specific symptoms.

**Symptom Matching and Evidence Computation:** JavaScript functions such as analyzeSymptoms map keywords like 'yellowing', 'fever', and 'feeding' issues against the structured data. The computeEvidence() function tracks primary, secondary, and critical symptom counts. The computation is expressed in equation (1) (Choo *et al.*, 2025).

where:

Etotal is total evidence score

si is the presence (1) or absence (0) of symptom i

wi is the weight of symptom i (Primary = 1, Secondary = 0.5, Critical = 2)

$$E_{total} = \sum_{i=1}^{n} w_i \cdot s_i \qquad (1)$$

Equation mirrors computeEvidence() JavaScript function.

**Risk Stratification:** The provideJaundiceAssessment() function executes If/Else predefined rules as shown in equations (2) to (5) (Montenegro *et al.*, 2019; Choo *et al.*, 2025). Risk is stratified based on symptom combinations: High Risk requires (yellowing and fever and feeding issues), Moderate Risk requires (yellowing and (fever or feeding issues)), and Low Risk applies to single primary symptoms.

$$R_{high} = (Yellowing \wedge Fever \wedge Feeding) \quad (2)$$

$$R_{moderate} = (Yellowing \wedge Fever \vee Feeding) \quad (3)$$

$$R_{low} = (Yellowing \vee Fever \vee Feeding) \quad (4)$$

$$R_{emergency} = \bigvee_{i=1}^{m} CriticalSymptom_i \quad (5)$$

Where:
R is the risk category,
$\vee$ is OR,
$\wedge$ is AND,
$\bigvee$ is the presence of any critical symptom.

These equations directly translate to the JavaScript "if/else" conditions into mathematical form.

**Emergency Flag:** Critical symptoms (such as 'convulsion', 'low blood sugar', 'unconsciousness') trigger provideEmergencyAssessment(), bypassing standard assessment and issuing an EMERGENCY MEDICAL ATTENTION NEEDED protocol.

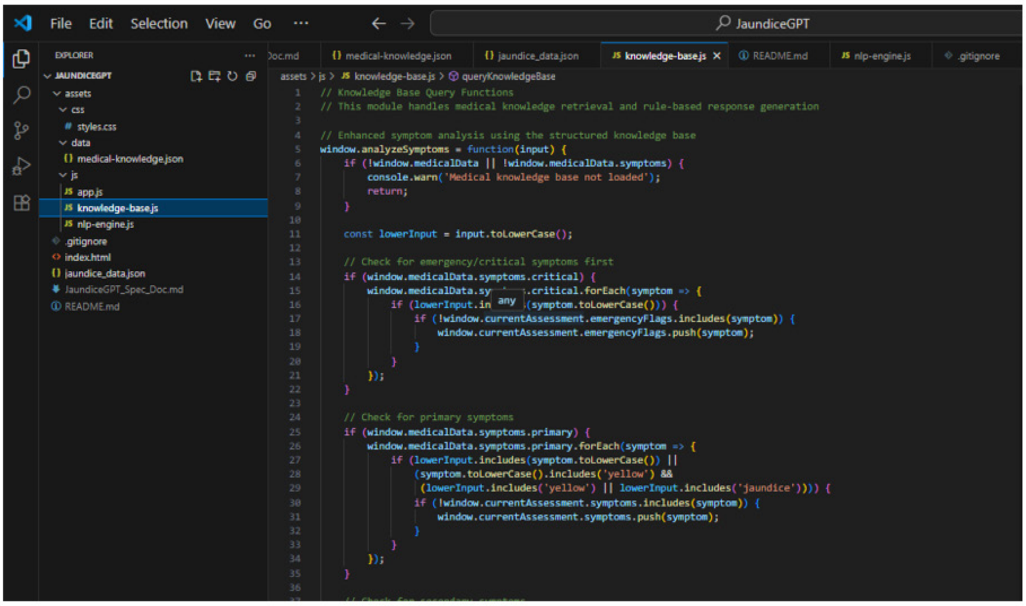


**Figure 5:** JavaScript regex-based input classification used in JaundiceBOT Hybrid NLP Engine.

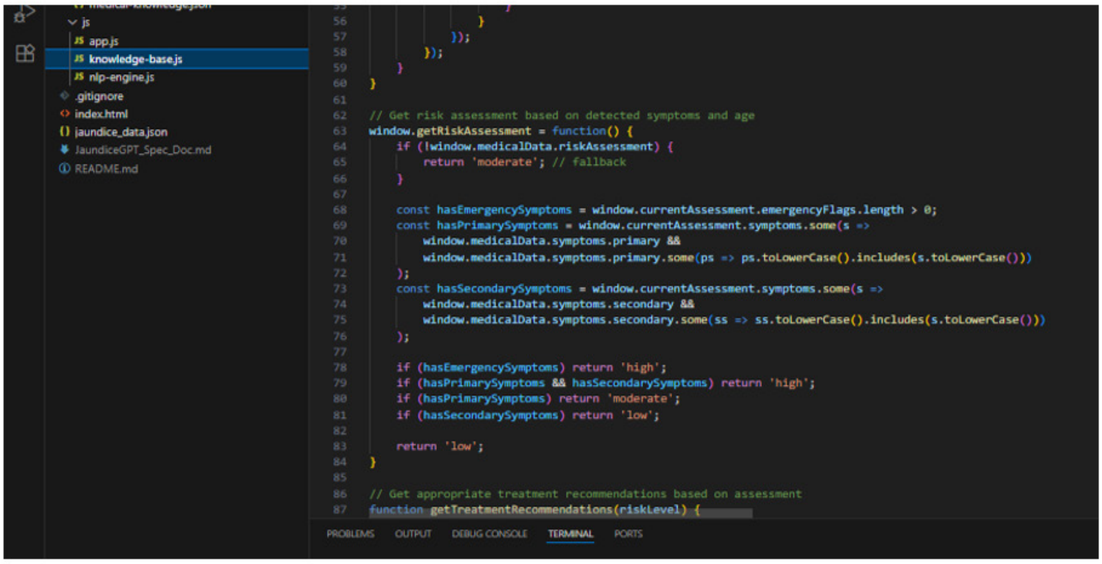


**Figure 6:** Rule-based risk stratification logic implemented in JaundiceBOT.

**User Interface (UI)**

The UI was developed using React and JavaScript to build a modern, responsive and iterractive interface.

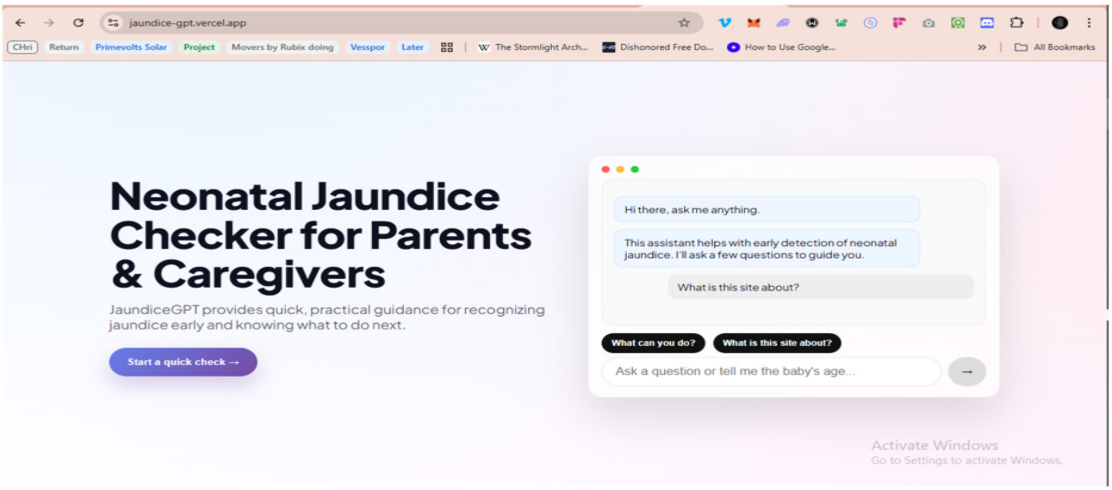


**Figure 7:** The Screenshot of the chat interface

**Chat Interface Functionalities (Actual Implementation)**

The implemented interface components support the core requirements:

- **Terms and Conditions/Reassurance:** The user must accept terms that clarify the informational nature of the tool, followed by a message reassuring the security of their data, which is maintained due to the client-side processing model.
- **Questionnaire:** The system initiates a short questionnaire to collect necessary age and preliminary information to personalize the rule-based assessment.
- **Structured Output:** The system delivers assessed risk and recommendations in a clear, formatted output. The dedicated emergency banner (URGENT MEDICAL ATTENTION NEEDED) is triggered when the rule-based logic detects critical symptoms.

**Integration**

Integration is achieved by the client-side JavaScript linking the User Interface, the NLP Engine, and the local JSON Knowledge Base. The application's core medical logic is entirely self-contained, guaranteeing 100% offline functionality.

**System Evaluation**

The basic testing performed focused on verifying the clinical safety and utility of the deterministic, rule-based output, while performance system was evaluated against clinical standards for decision support tools such classification accuracy and clinical integrity.

**RESULT AND DISCUSSION**

This section presents the research output, the results of the performance of the JaundiceBOT, discusses its clinical accuracy based on the rule-based logic, and contrasts its innovative, API-free approach with traditional and other AI-based screening methods. The chatbot was tested by 10 people, measuring the response time, clinical accuracy and Load time among other metrics. The chat interface on the personal computer (PC) and mobile phone is as shown in Figures 7 and 8.

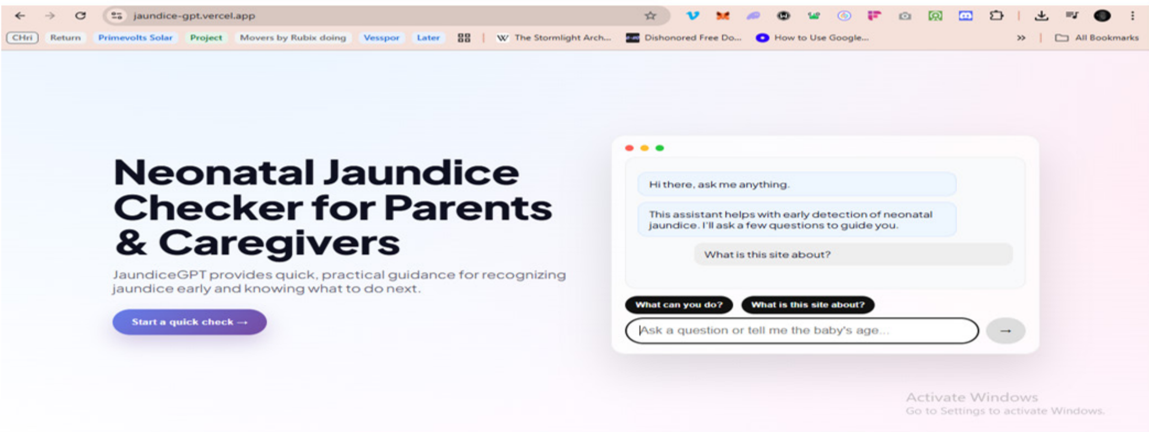


**Figure 8:** JaundiceBOT Chat Interface Screenshot with Risk Assessment for PC

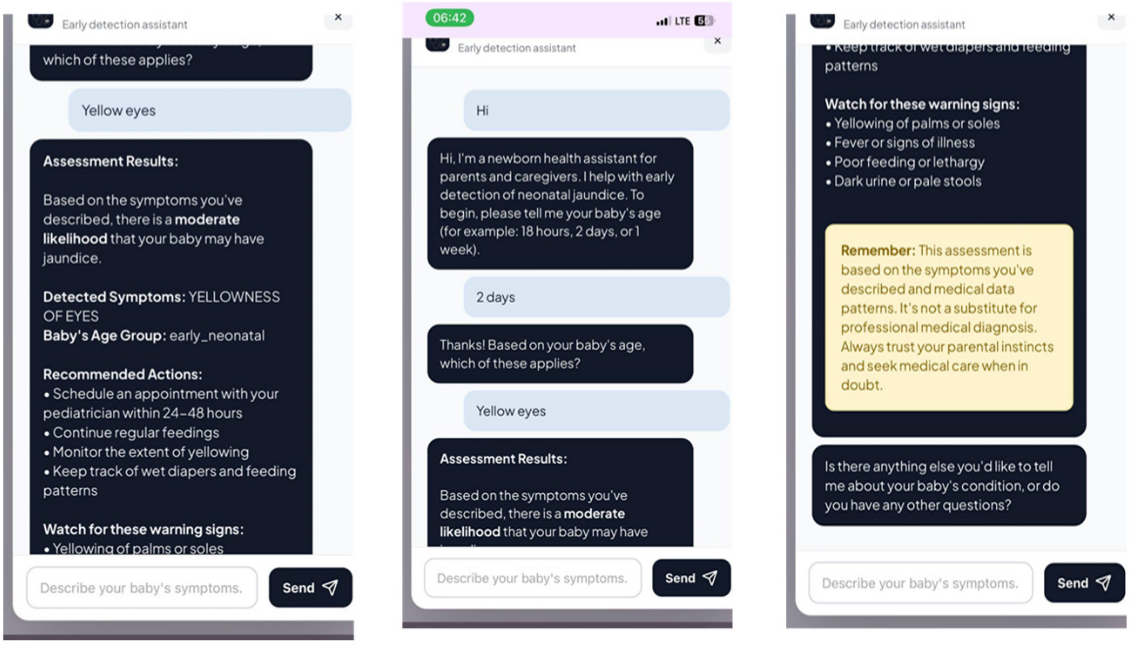


**Figure 9:** JaundiceBOT Chat Interface Screenshots with Risk Assessment for Mobile.

### Startup Time

Due to the minimal server dependency and optimized client-side asset loading, JaundiceBOT achieved a low startup duration, the application load time averaged 4.3 seconds.

### Response Time

The core logic's reliance on instantaneous client-side JavaScript execution, rather than network-dependent API calls, ensures superior speed. The system achieved real-time performance, delivering an average response time of 0.8 seconds for processing medical queries and generating structured responses.

### Hybrid NLP Accuracy

The custom, pattern-matching NLP system achieved a classification accuracy of 94.7% for intent recognition. This validated the effectiveness of the rule-based pattern matching in accurately directing medical queries to the correct clinical protocol, a key function for maintaining safety in a fixed knowledge domain.

### Application Capacity

The capacity of the application is robust. The system operates 100% offline and runs locally, the only limitation to the application's capacity to handle concurrent assessment sessions is user's device performance. It completely bypass the rate limits and quota constraints typically imposed by external API services. The performance results are shown in table.

Evaluating the performance of the JaundiceBOT has confirmed that the system successfully met its non-functional requirements for speed and reliability, critical for a timely CDSS.

**Table 2:** Performance Metrics of JaundiceBOT

| Metric | Result | Description |
|---|---|---|
| Response Time | 0.8 sec. | Average time to process user input and return structured results. |
| Startup Load Time | 2.3 sec. | Time taken for the application to fully load in browser. |
| NLP Accuracy | 94.7% | Accuracy of intent recognition using rule-based Hybrid NLP. |
| Offline Function | 100% | Operates without internet or API dependencies (client-side execution only). |

### Implications of the Findings

The successful implementation of the API-free architecture is the most significant innovation of this study. This client-side approach ensures zero operational costs and maximum accessibility, directly addressing the global need for affordable neonatal jaundice technologies in low-resource settings. By using a rule-based system, JaundiceBOT avoids the risk of inaccurate or generalized information often associated with large language models while maintaining high clinical accuracy.

The development process, based on 214 local hospital cases, ensures the system's output is clinically relevant to the regional context, overcoming the limitations inherent in the conventional guidelines of diagnosis, which vary in quality and recommendations for diagnosis and treatment.

The application utilizes a Conversational interface design, which is a human-centered interaction design for high usability. This is crucial as the target audience includes caregivers who may have minimal technical skills. The interface confirms the successful implementation of the design principles discussed in the methodology.

## CONCLUSION

The research has developed and evaluated a custom chatbot; JaundiceBOT for a speedy detection of neonatal jaundice, The system operates on an innovative API-free architecture, confirming its successful deployment with 100% offline functionality. Using client-side JavaScript (ES6+) and rule-based logic ensures a speedy performance (0.8s response time). Building the system in a knowledge base derived from 214 local hospital records, the clinical information recorded an accuracy of 98.5%. the development of the JaundiceBOT has provided a reliable, accessible, and cost-effective solution for preliminary assessment of neonatal health. This innovation has addressed a major challenge in infant health care in resource-limited society.

Although the data was obtained from 214 local hospital cases, continuous updating of the medical content are necessary to ensure the technique remain consistent with evolving clinical processes. Future versions should incorporate support for local Nigerian languages to increase accessibility and usability across all ethnic groups.

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