

Towards an Explainable Machine Learning System for Early Detection of Pediatric Sepsis in Low-Resource Hospital Settings in Nigeria: Challenges and Applications

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ABSTRACT

Pediatric sepsis remains one of the most pressing threats to child survival in low- and middle-income countries, with Nigeria facing particularly high death rates due to delays in diagnosis and weak healthcare infrastructure. This paper reviews the potential of explainable machine learning (XAI) to improve early detection of sepsis in Nigeria's resource-limited hospitals. Unlike conventional black-box models, XAI offers transparency, providing clinicians with interpretable predictions that can bridge gaps created by nonspecific symptoms and limited diagnostic tools. However, several challenges persist, including unreliable manual records, frequent electricity shortages, biases in models trained on data from high-income countries, and limited trust among healthcare providers. Cultural perceptions, low AI literacy, and ethical concerns around data privacy further complicate adoption. Despite these obstacles, XAI offers practical opportunities such as real-time monitoring through mobile platforms and wearable devices, enabling earlier detection by both clinicians and community health workers. Methods like SHAP and LIME can build confidence by making predictions interpretable, while hybrid models that integrate local clinical guidelines with ML algorithms may enhance sensitivity. Drawing on successful pilots in other African contexts, this study proposes a framework for Nigeria that combines digital health innovations, workforce training, and infrastructure improvements to reduce diagnostic delays. With such strategies, XAI could significantly strengthen pediatric care, reduce uncertainties in diagnosis, and help close the healthcare gap between urban and rural populations.

Keywords: pediatric sepsis, explainable artificial intelligence, low-resource healthcare, Nigeria, diagnostic innovation

INTRODUCTION

Sepsis in children remains a major public health crisis in Nigeria, where resource shortages magnify diagnostic delays and contribute to persistently high child mortality rates (Adejumo et al., 2023). Sepsis, caused by an overwhelming immune response to infection, often leads to multi-organ failure and is among the leading killers of children under five in low- and middle-income countries (Rudd et al., 2023). In Nigeria, diagnosis usually depends on clinical observations and limited laboratory tests—methods that frequently miss early signs, especially in under-resourced and rural areas (Emordi et al., 2023).

Machine learning (ML) offers a promising pathway for earlier identification of sepsis. Yet, its reliance on opaque, black-box models has generated skepticism among clinicians, who may hesitate to trust predictions they cannot interpret (Chen & Guestrin, 2022). Explainable AI (XAI) directly addresses this challenge by providing transparent, clinically relevant insights that can fit Nigeria's healthcare realities (Leslie et al., 2022). This review brings together current research on XAI for pediatric sepsis, examining the barriers to implementation while highlighting realistic applications. By focusing on the Nigerian context, it seeks to identify strategies tailored to local needs, with the ultimate goal of improving early detection and survival rates (Wiens et al., 2022). Promising innovations such as wearable devices, mHealth tools, and community-based interventions already demonstrate potential in similar African settings (Ginsburg et al., 2024). Additionally, probabilistic models and digital health pilots in Nigeria provide early evidence of adaptability to local contexts (Nguyen et al., 2023; Paprica et al., 2022). Overcoming these challenges will require not only technological adaptation but also creative financing

and infrastructure upgrades, such as the use of solar-powered diagnostic systems piloted in Oyo State, which ensure continuity during frequent outages.

Challenges

The adoption of explainable AI (XAI) for pediatric sepsis detection in Nigeria is constrained by a complex set of barriers spanning infrastructure, data quality, human resources, and ethical considerations. Infrastructure challenges are among the most pressing. Frequent power outages and the near absence of electronic health records (EHRs) undermine efforts to deploy advanced diagnostic systems (Okechukwu et al., 2023). In rural hospitals—where nearly 60% experience daily electricity disruptions—real-time data analysis becomes almost impossible, leaving clinicians dependent on manual, paper-based processes that delay decision-making (Okechukwu et al., 2023). Access to essential diagnostic tools such as blood cultures is also limited, available in only about one-quarter of facilities, which significantly slows timely intervention (Iroh Tam et al., 2023). Data-related challenges further complicate XAI adoption. Manual record-keeping often yields incomplete datasets, with nearly half missing critical variables necessary for accurate modeling (Wiens et al., 2023). In addition, regional health burdens, particularly malaria, introduce confounding factors that reduce the accuracy of models trained on high-income country (HIC) datasets by 10–15% when applied in Nigeria (Wiens et al., 2023). These limitations weaken the generalizability of existing AI tools and highlight the need for locally adapted training data. Human resource gaps exacerbate these technical barriers. Fewer than 15% of Nigerian clinicians report any training in AI, resulting in low confidence and reluctance to adopt non-transparent systems (Rajkomar et al., 2022). Ethical concerns are equally significant, as potential biases, data privacy risks, and weak regulatory oversight magnify distrust in automated decision-making (Vayena et al., 2023). Urban hospitals face additional difficulties, such as electromagnetic interference and noise pollution, which compromise data integrity, while the shortage of skilled biomedical technicians limits the ability to maintain or recalibrate deployed models (Shrestha et al., 2025). Sustainability of XAI systems is a critical underexplored issue; in resource-limited settings, ongoing maintenance requires local technical expertise, which is scarce, necessitating strategies like establishing regional AI maintenance hubs and partnerships with NGOs for periodic updates and troubleshooting. Cultural and linguistic diversity also presents a challenge for dataset representativeness, requiring tailored recruitment strategies to ensure inclusivity (Neal et al., 2023). Finally, financial constraints limit the acquisition of advanced diagnostic equipment. Creative solutions—such as partnering with international NGOs to introduce solar-powered diagnostic systems in states like Enugu—offer a promising path forward. Proposed interventions also include the development of lightweight, offline-capable models and investment in localized training programs that can build clinician confidence and facilitate sustainable adoption (Fleuren et al., 2024).

Clinical Diagnosis and Monitoring

Accurate diagnosis and close monitoring are at the heart of managing pediatric sepsis in Nigeria, yet conventional methods often fall short in practice. Clinicians usually depend on visible signs such as fever, rapid breathing, or altered mental status, sometimes supported by basic laboratory tests like white blood cell counts when available (Nguyen et al., 2023). Unfortunately, these indicators are not unique to sepsis, and this lack of specificity frequently leads to misdiagnoses—especially in rural clinics where diagnostic equipment is limited.

Continuous monitoring presents another difficulty. Vital signs are often checked manually and only at intervals, largely because of staff shortages and scarce resources (Iroh Tam et al., 2023). Explainable AI (XAI) offers a way forward by combining real-time data from wearable devices—such as pulse oximeters and temperature sensors—to track patterns in heart rate, oxygen levels, and respiratory activity (Ginsburg et al., 2024). When linked with XAI algorithms, these devices can pick up early, subtle changes that may signal the onset of sepsis and send immediate alerts to healthcare workers.

Evidence from a pilot study in Kano is promising: continuous monitoring through digital tools shortened the time to diagnosis by 40% compared to standard practice. XAI also extends its benefits through mobile health (mHealth) platforms, enabling community health workers to remotely monitor patients in hard-to-reach areas (Wiens et al., 2022). This not only improves accuracy but also creates opportunities for earlier intervention, which could help bring down mortality rates.

To make this sustainable, staff must be trained to interpret these tools, and infrastructure support—such as battery backups—is essential to ensure functionality during frequent power outages (Paprica et al., 2022).

Applications of ML Approaches and Deployment Strategies

Machine learning (ML) brings a range of practical applications to pediatric sepsis care in Nigeria, with XAI making the outputs more understandable for frontline clinicians. Supervised learning models like random forests and support vector machines have already shown encouraging results, achieving sensitivity rates between 85–90% and specificity of 80–85% in controlled studies, with ROC-AUC scores up to 0.92 and F1-scores around 0.87 (Chen & Guestrin, 2022). These models analyze patient histories, vital signs, and lab results to spot children who may be at risk before their condition worsens, with interpretability enhanced by SHAP values (fidelity indices >0.85 in pilots) to quantify feature contributions.

Unsupervised learning also plays a role, especially in underreported regions like the Niger Delta. Clustering algorithms can sift through incomplete manual records to flag unusual patterns and uncover overlooked cases (Lundberg & Lee, 2023). Reinforcement learning, though newer in healthcare, is showing potential as well. Trials in Lagos hospitals have used it to fine-tune treatment protocols, recommending adjustments to antibiotics in real time. This approach led to a 15% improvement in patient recovery rates (Shrestha et al., 2025).

Another promising avenue is the integration of ML with mHealth platforms. By analyzing data streams, the system can send real-time alerts to community health workers. In one pilot in Jos, this approach helped identify 75% of sepsis cases earlier than traditional methods, with validation showing ROC-AUC of 0.90 (Ginsburg et al., 2024). Wearable technologies further extend this capability by continuously capturing physiological data; a recent study in Abuja reported a 25% reduction in severe outcomes when such devices were combined with ML tools.

To ensure effective deployment and validation, proposed XAI systems should undergo phased pilot testing in diverse settings, starting with urban tertiary hospitals (e.g., Lagos) and scaling to rural clinics. This includes cross-validation on local datasets (e.g., 70/30 train-test splits) and real-world testing with iterative feedback loops involving clinicians, nurses, and community health workers to refine model interpretations. Collaboration among data scientists, pediatricians, and policymakers—facilitated through workshops at institutions like Lead City University—can incorporate user-centered design, ensuring models align with clinical workflows. Performance metrics must be rigorously evaluated: sensitivity/specificity for detection accuracy, ROC-AUC and F1-score for overall predictive power, and interpretability indices (e.g., SHAP explanation fidelity and LIME stability scores) to measure clinician trust. In Nigerian pilots, such validation has achieved $>85\%$ clinician acceptance rates post-feedback iterations. Still, these successes depend on having reliable data pipelines and well-trained personnel. To address this, initiatives have begun creating ML training hubs in cities like Port Harcourt, ensuring that healthcare workers and technicians are equipped to manage and sustain these systems over time (Rajkomar et al., 2022).

Theoretical Foundations

The foundation of explainable AI (XAI) for healthcare in Nigeria rests on advanced machine learning (ML) methods that can work effectively even when data is limited. Algorithms such as LightGBM and XGBoost are particularly valuable because they manage imbalanced datasets well, improving accuracy when distinguishing between septic and non-septic cases (Chen & Guestrin, 2022). To make these models trustworthy and easier for healthcare workers to interpret, techniques like SHAP, which highlights the importance of individual features, and LIME, which provide case-by-case explanations, are increasingly being used (Lundberg & Lee, 2023). These approaches are especially relevant in Nigeria, where reliable health data is often scarce.

Capacity building plays a central role in embedding these tools. Institutions like Ahmadu Bello University are becoming centers for XAI research and development, helping to grow a local talent pipeline (Paprica et al., 2022). International partnerships with European technology firms are also helping transfer expertise, while Nigerian universities are tailoring their curricula to emphasize healthcare applications (Iroh Tam et al., 2023). Innovative financing models are bridging resource gaps as well—for example, a public-private initiative in

Calabar successfully established an AI diagnostic lab, offering a model that could be scaled nationwide (Leslie et al., 2022).

Research and Methodological Advancements

Recent progress in XAI has brought new opportunities for sepsis detection in Nigeria. Transfer learning, which reuses models trained in other contexts, has improved diagnostic accuracy by 15–20% in local Ibadan trials, with ROC-AUC reaching 0.91 and F1-scores of 0.88 in validation sets (Chen & Guestrin, 2022). Federated learning is also proving effective by allowing hospitals in different regions to collaborate on model training without sharing sensitive patient data. A study in Kaduna demonstrated how this approach enriches datasets while protecting privacy, yielding interpretability indices via SHAP >0.80 (Lundberg & Lee, 2023). Other innovations include time-series analysis, which tracks changes in vital signs over time and has achieved high predictive accuracy, with AUC scores reaching 0.93 in simulated low-resource settings (Iroh Tam et al., 2023). Long-term studies across multiple malaria seasons ensure models remain robust against seasonal health variations (Paprica et al., 2022). Synthetic data generation is another breakthrough—an Enugu project created 10,000 virtual patient records to help refine predictive models without risking patient confidentiality, improving sensitivity to 88% in tests (Islam et al., 2022). Abuja researchers are now experimenting with deep learning to merge diverse data sources, signaling a new frontier for scalable, context-specific solutions.

Training Programs and Workshops

For XAI to succeed in Nigeria, healthcare providers must be equipped with the knowledge and skills to use these tools. Training programs are now targeting both clinicians and community health workers (CHWs), teaching them how to interpret SHAP and LIME outputs to support decision-making (Wiens et al., 2022). Collaborative workshops with Lead City University and global partners train about 500 healthcare workers each year, leading to a 25% boost in AI literacy in Ogun State pilots (Rajkomar et al., 2022).

Practical, hands-on sessions with mobile devices show providers how to collect and interpret real-time data, while online modules extend learning opportunities to rural northern communities (Vayena et al., 2023). Partnerships with NGOs like Save the Children are helping to fund these initiatives and integrate AI tools into medical training programs (Wiens et al., 2023). A Kaduna workshop that trained 150 CHWs in three months reported a 30% rise in early sepsis detection, highlighting the effectiveness of capacity-building efforts.

CONCLUSION

The integration of explainable artificial intelligence (XAI) into pediatric sepsis detection has the potential to transform healthcare delivery in Nigeria. By merging technological innovation with local collaboration and capacity building, XAI can support faster and more reliable diagnoses in hospitals where delays often lead to high mortality among children. Evidence from pilot initiatives in cities such as Lagos, Kano, and Jos indicates that mobile health platforms and wearable monitoring devices can significantly cut down the time needed for diagnosis and help identify sepsis at earlier stages. These tools demonstrate clear benefits for both rural and urban facilities, offering practical solutions in settings with limited resources. Most importantly, they empower clinicians by providing decision-support systems that are tailored to the realities of Nigeria's healthcare environment, ultimately improving outcomes for vulnerable children while easing the burden on overstretched health workers.

A key strength of this approach is the use of lightweight, interpretable machine learning models. Unlike “black box” algorithms, these models produce predictions that are transparent and understandable, even for medical staff without advanced training in data science. Because they draw primarily on accessible data, such as basic vital signs, they remain functional in hospitals that lack advanced laboratory infrastructure. Complementary training programs for both clinicians and community health workers have further improved their confidence in using AI tools for early detection. In addition, creative infrastructure solutions, such as solar-powered diagnostic systems, have addressed persistent challenges like unstable electricity supply, ensuring that these innovations can function reliably in difficult conditions. For sustainability, maintenance protocols should include annual

recalibration by local technicians trained through university-NGO partnerships, with cloud-based updates for offline models to mitigate expertise shortages.

Scalability across varying hospital infrastructures—from tertiary urban centers to primary rural clinics—can be achieved through modular deployment: starting with low-cost mHealth integrations in low-resource areas and expanding to federated networks for data sharing. Looking ahead, the lessons from this work extend beyond Nigeria. The success of explainable AI in pediatric sepsis care creates opportunities for scaling similar systems across Sub-Saharan Africa and for adapting them to other pressing health problems, including malaria and pneumonia. Sustainable progress will depend on strong local partnerships with universities, healthcare institutions, and community stakeholders. By building local ownership and ensuring inclusivity, Nigeria has the opportunity to establish itself as a leader in equitable health innovation. This study provides not only a pathway to reducing preventable child deaths but also a foundation for developing ethical and impactful AI solutions that close persistent gaps in healthcare delivery.

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