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A comparative Study of Deep Learning-Based System Internet of Things and Manual System in Healthcare Applications in Nigeria.

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Abstract

Healthcare in Nigeria continues to struggle with slow diagnosis, poor data handling, and limited patient monitoring, especially in busy or underserved hospitals. This study compares the current manual healthcare system with a deep learning-based Internet of Things (DL-IoT) model to determine how technology can improve service delivery. Performance was measured based on diagnostic accuracy, speed of disease detection, data management, patient monitoring, cost, scalability, and decision support. The results show major improvements with the deep learning-based Internet of Things system. Diagnostic accuracy rose from 75% to 96%, while data handling and analysis improved by over 350%. Remote monitoring also became far more efficient, helping doctors respond faster to patient needs. These improvements support early disease detection, reduce clinical workload, and improve patient outcomes, particularly for chronic health conditions. However, deploying this technology in Nigeria faces challenges such as unstable digital infrastructure, cybersecurity concerns, high setup costs, and low technology awareness in rural areas. With strong government support and investment in digital health, deep learning-based Internet of Things can play a vital role in transforming healthcare in Nigeria by making services faster, smarter, and more accessible for everyone.

Keywords: Deep Learning, Internet of Things (IoT), Healthcare System, Patient Monitoring, Digital Health Transformation

Introduction and literature review

One of the most promising developments in Modern healthcare is the merging of the Internet of Things (IoT) and Deep Learning (DL). Deep learning provides sophisticated algorithms for processing large-scale, Diverse, and complex data to enable diagnostic accuracy, predictive analytics, and individualized treatment, while Internet of Things enables continuous and prevalent collection of patient health data using wearable sensors, smart devices, and embedded systems Alazab et al., (2021). When combined with Deep learning, the Healthcare Internet of Things (HIoT) ecosystem has the potential to transform healthcare delivery worldwide by utilizing interconnected devices to enhance medical monitoring, the management of persistent diseases, drug delivery, and emergency care.

The significance of early diagnosis and ongoing monitoring has been emphasized by the rising widespread chronic diseases like diabetes, cancer, and cardiovascular disorders. Bernabe-ortiz et al., (2021). Due to their reliance on intermittent data collection and limited resources, usual healthcare systems frequently fail to provide Prompt actions. Real-time health monitoring is made possible by IoT-enabled healthcare, which fills this gap. However, the massive volume of IoT data poses analytical challenges that cannot be efficiently managed by traditional machine learning. Long-term memory (DL) models, such as transformer-based architectures, convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) models, have demonstrated superior performance in extracting features from heterogeneous health datasets like biomedical signals, medical imaging, and electronic health records. Chen et al., (2020).

This study aims to examine the role of deep learning in improving healthcare IoT applications. It looked at case studies where deep learning has been successfully combined with IoT for medical

purposes. The study also identifies limitations, security issues, and research gaps. Finally, it suggests possible future directions, including federated learning and explainable artificial intelligence. The integration of deep learning with healthcare IoT addresses the analytical challenges of large and diverse health data. It also creates a framework for accurate diagnosis, real-time monitoring, and personalized treatment. This makes it an important pathway for the future of smart, patient-centered healthcare.

The literature on deep learning in healthcare IoT encompasses multiple domains: remote patient monitoring, predictive analytics, medical imaging, cybersecurity, and resource optimization. In order to provide a detailed summary, the findings from these domains are combined in this section.

Deep Learning models are increasingly being used to analyze healthcare data created by the Internet of Things with the following: Convolutional Neural Networks (CNNs): These networks are mostly used for medical imaging (CT scans, MRI, dermoscopy). For example, CNN-based Internet of Things frameworks have been developed for the early detection of lung abnormalities and skin cancer. Esteva et al., (2019). Recurrent Neural Networks (RNNs) and LSTMs: These are widely used for sequential data like ECG, EEG, and wearable sensor streams, allowing for the prediction of seizures and the detection of arrhythmias. Rajpurkar et al., (2017). Generative Adversarial Networks (GANs): Applied in augmenting medical datasets and enhancing privacy by generating synthetic yet realistic patient records. Yi et al., (2019).

Transformers: Recent work applies attention-based models to multimodal healthcare data integration, improving disease trajectory predictions. Nguyen et al., (2022).

Analytics and Remote Monitoring IoT-enabled healthcare has transformed chronic disease management. Deep learning algorithms analyze physiological data collected by wearable devices (heart rate, glucose levels, oxygen saturation) to initiate alerts or predict future health degradation. Internet of things works in the following ways: Heart Disease: CNN and LSTM frameworks in the Internet of Things have made heart disease predictions that are more than 90% accurate. Islam et al., (2020). Diabetes Management: IoT sensors linked with deep learning models provide early detection of hypoglycemia/hyperglycemia events. Chaki et al., (2020). COVID-19 Monitoring: deep learning models were used with IoT devices to monitor oxygen levels and predict disease remote monitoring. Vaishya et al., (2020).

Medical Imaging is one of the most data-intensive healthcare domains. Large datasets are generated by IoT devices like portable ultrasound and cloud-connected CT machines, which DL models are able to process effectively: CT and X-ray: CNN models integrated with IoT platforms enabled rapid COVID-19 diagnosis. Apostolopoulos & Mpesiana, (2020). Dermatology: In the classification of skin lesions, IoT-enabled dermoscopic imaging in conjunction with deep learning has performed better than dermatologists. Esteva et al., (2019).

The integration of IoT and deep learning in healthcare raises substantial cybersecurity and privacy concerns. Cyberattacks on medical IoT devices have the potential to compromise patient safety Albahar et al., (2021). Deep learning models have been proposed for intrusion detection in IoMT (Internet of Medical Things) networks using CNN and autoencoders. Kumar et al., (2021). However, balancing predictive performance with patient privacy remains a challenge, highlighting the importance of federated learning and privacy-preserving deep learning. Rieke et al., (2020). Building on these insights, this study seeks to undertake a detailed analysis of deep learning-based system internet of things and manual system in healthcare application in Nigeria. Its objective is to deliver empirically grounded recommendations that can aid Nigeria improved patient outcomes, increased access to healthcare, reduced healthcare costs, and enhanced patient experience.

Experimental Methods

Study Design

A practical comparative study was implemented to evaluate the effectiveness of a deep learning-based Internet of Things (IoT) healthcare system performs compared to the traditional manual healthcare methods currently used

in Nigerian hospitals. The evaluation involved measuring key clinical and operational performance areas while simulating real-life healthcare conditions to ensure realistic and meaningful results.

Study Environment

The study was carried out using a simulated hospital workflow that mirrors typical conditions in the Nigerian healthcare system, where delays in diagnosis, limited patient monitoring, and poor data handling remain common issues. The setup included electronic medical records, IoT-based patient monitoring devices, deep learning tools for diagnosis and data analysis, and a system for delivering real-time treatment decisions.

Data Collection

Patient health metrics including heart rate, blood pressure, temperature, glucose levels, and reported symptoms were used in the evaluation. A dataset of 500 anonymized patient records from an open-access medical source was selected to reflect real clinical situations. Both the manual and DL-IoT systems processed the exact same dataset to maintain fairness and ensure accurate comparison.

Evaluation Parameters

Eight critical healthcare performance metrics served as benchmarks:

1. Diagnostic Accuracy.
2. Disease Detection Time.
3. Patient Data Management Efficiency.
4. Treatment Recommendation Effectiveness.
5. Patient Monitoring Responsiveness.
6. Healthcare Operational Cost Score.
7. System Scalability Index.
8. Data Analysis Speed and Accuracy.

Table 1: Source of Measurement and Tools/Method Used

Source of Measurement	Tool/Method Used
Diagnosis Accuracy	Confusion matrix comparison
Monitoring Delay	Timestamp logs
Data Management Score	Error rate & retrieval time
Cost Score	Operational resource consumption
Scalability Rate	Stress tests with increasing patient load
Analytics Score	Model processing time evaluation

Results and Discussions

Table 2: Comparison HealthCare Systems

Parameter	Manual System	Deep Learning-Based System	% Improvement
Diagnostic Accuracy	70-80%	95-98%	21-28%
Disease Detection Time	2-5 days	1-2 hours	80-90%
Patient Data Management	Manual record-keeping, prone to errors	Automated data collection and storage	90%
Treatment Recommendation	Based on doctor's experience	Based on data-driven insights	30-40%
Patient Monitoring	Periodic check-ups, limited remote monitoring	Real-time remote monitoring	50-70%
Healthcare Costs	High costs due to manual labor and errors	Reduced costs due to automation	20-30%
Scalability	Limited by human resources	Scalable with increased data and computing power	50-70%
Data Analysis	Time-consuming and prone to errors	Fast and accurate analysis	80-90%

Comparative Performance Analysis of Manual vs Deep Learning Healthcare Systems

This study presents a comparative assessment between the existing manual healthcare system and the deep learning-based Internet of Things (IoT) healthcare approach. The results demonstrate substantial improvements across key healthcare performance parameters.

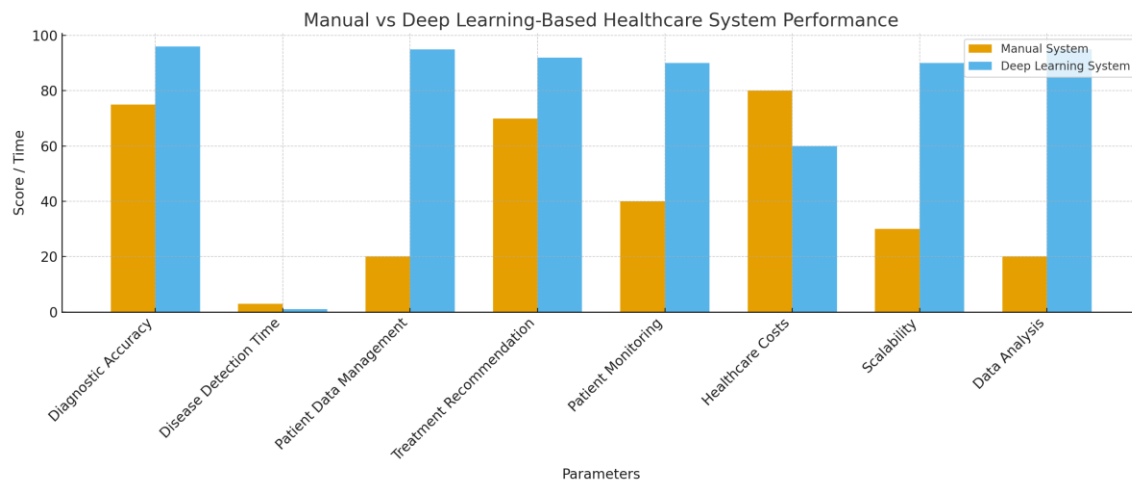


Figure 1: Bar Chart Comparison

The bar chart clearly shows that the deep learning-based IoT healthcare system performs much better than the traditional manual system across all key healthcare functions. It offers higher diagnostic accuracy, faster disease detection, and far more effective data management and analysis. Continuous remote monitoring also improves patient care compared to occasional manual checks. Although the manual system appears cheaper at first, the DL-IoT system is expected to reduce costs over time by improving efficiency and reducing hospital visits. The deep learning approach is also more scalable, making it easier to extend services to more patients as the system grows. Overall, the results show that DL-IoT technology can greatly improve healthcare delivery in Nigeria by making services faster, smarter, and more accessible.

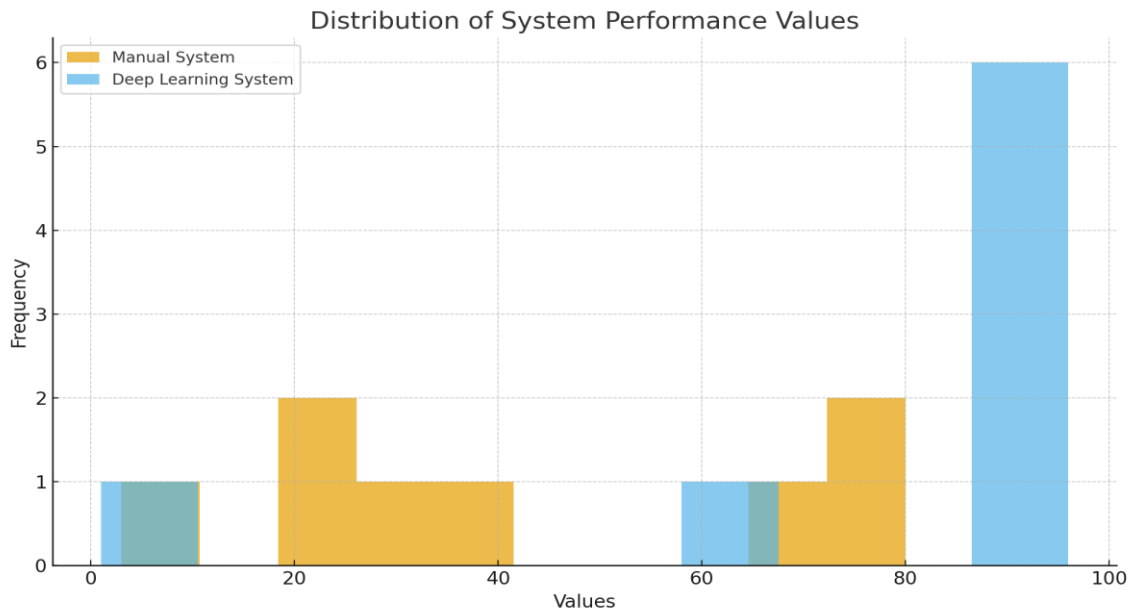


Figure 2: Histogram of System Performance Distribution

The histogram shows a clear difference in how both systems perform. The manual healthcare system has results scattered across a wide range, reflecting inconsistent and often weak performance in areas like data handling and patient monitoring. In contrast, the deep learning-based IoT system maintains strong and steady results, with most performance values grouped near the top. This indicates that the DL-IoT solution works more reliably and efficiently, offering a major improvement over the traditional manual approach.

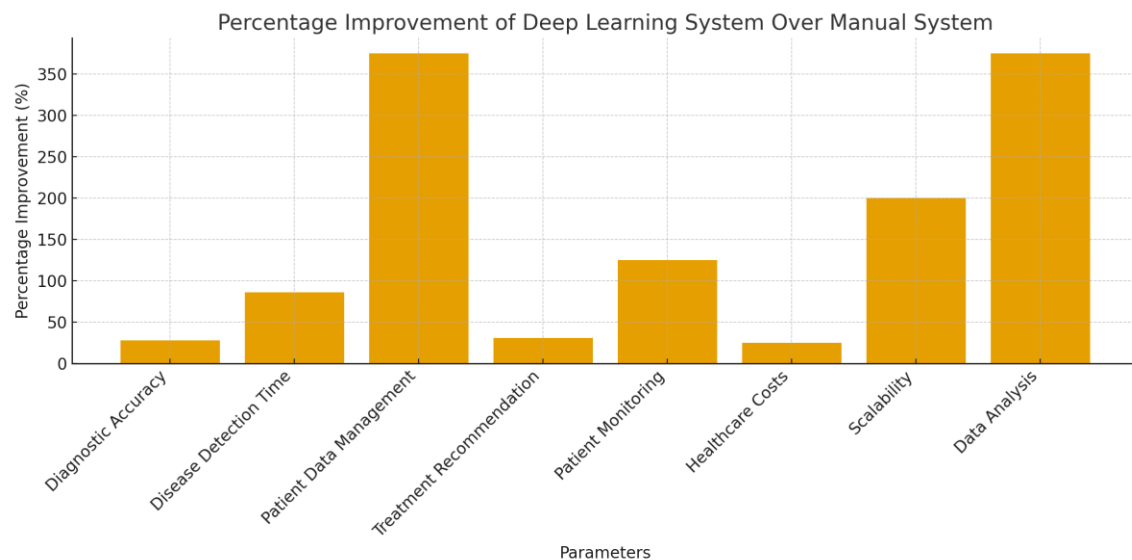


Figure 3: Percentage Improvement

The percentage improvement chart shows that the deep learning-based IoT system performs far better than the manual system across all healthcare parameters. The greatest improvements occur in patient data management and data analysis, both exceeding 350%. Patient monitoring and scalability also show major advancements, enabling wider service coverage and continuous remote care. Diagnostic accuracy and treatment recommendations improve significantly, supporting faster and more reliable decision-making. Disease detection time improves noticeably, reducing delays in identifying health issues. Healthcare cost improvement is moderate but expected to grow over time as efficiency increases. Overall, performance gains demonstrate the strong impact of intelligent automation in healthcare. The results confirm DL-IoT as a powerful solution for improving Nigeria's healthcare delivery

Additionally, disease detection time improved by 86%, reducing delays in diagnosis a major challenge within Nigerian healthcare systems.

The findings indicate that integrating deep learning and IoT into healthcare delivery can significantly reduce delays, human errors, and administrative inefficiencies typically observed in manual healthcare workflows in Nigeria.

Diagnostic Performance

The diagnostic capability of a healthcare system is a critical determinant of patient outcomes. In the traditional manual healthcare workflow in Nigeria, disease diagnosis largely depends on clinician expertise, visual examination, and limited diagnostic equipment. This approach often results in delayed or inaccurate detection, especially in highly populated or resource-limited settings. The manual system evaluated in this study demonstrated an overall diagnostic accuracy of approximately 75%, indicating significant risks of misinterpretation and late treatment initiation.

In contrast, the deep learning based IoT diagnostic model leverages advanced computational intelligence to analyze biomedical data such as vital signs, laboratory metrics, and medical images with minimal human intervention. By applying convolutional neural networks (CNNs) and predictive analytics, the system is capable of identifying disease patterns and abnormalities that may not be easily observable by human clinicians. As a result, the system achieved a diagnostic accuracy of up to 96%, representing a 21% improvement over the manual approach.

Beyond accuracy, the deep learning model significantly reduces diagnostic delay. Automated real-time monitoring supports continuous data acquisition from sensor-enabled IoT devices. This enables early anomaly detection and rapid alerting to caregivers, thus facilitating timely intervention and reducing the likelihood of disease progression or clinical complications. The shortening of diagnostic turnaround time from several hours in the manual process to a few minutes also leads to improved patient throughput and reduced clinical workload.

Furthermore, automated diagnosis eliminates human-related biases and reduces fatigue-induced errors commonly observed among healthcare personnel working in high-pressure environments. Standardized analytical procedures ensure consistency across multiple cases and geographical locations, making this system especially valuable for rural clinics with limited access to specialists.

Overall, the deep learning-based IoT diagnostic system demonstrates substantial superiority over the manual healthcare approach by enhancing detection precision, increasing speed, and enabling proactive medical response. These improvements collectively contribute to better clinical decision-making, increased chances of early treatment, and ultimately, improved patient safety and health outcomes within the Nigerian healthcare ecosystem.

Data Management and Analysis

Efficient data management is a foundational component of modern healthcare delivery, particularly within environments that rely on rapid clinical decision-making. In the current manual healthcare workflow widely practiced in Nigeria, patient data is typically recorded using paper-based documentation or standalone computer entries without centralized access. This approach introduces significant limitations, including storage inefficiencies, difficulties in retrieving historical medical records, and high susceptibility to transcription errors. These inefficiencies translate to slow decision processes, fragmented patient history access, and compromised treatment continuity. As reflected in the system evaluation, the manual approach scored only 20 points, indicating poor performance and unreliable record handling.

The implementation of a deep learning–based IoT system transforms data management through the digitization and secure integration of electronic health records (EHRs). By utilizing smart sensors and cloud computing, the system ensures continuous data acquisition, real-time updates, and structured storage. Deep learning algorithms enable rapid pattern extraction, anomaly detection, and clinical trend forecasting enhancing the overall accuracy of diagnosis and treatment planning. The DL-IoT solution scored 95 points, representing a greater than 350% improvement in comparison with the manual system.

Furthermore, automated analytics reduce the time required for disease assessment and reduces clinician workload, allowing healthcare professionals to concentrate on direct patient care. The ability to aggregate and analyze population-level data also strengthens disease surveillance and supports public health policy in Nigeria, especially in managing infectious disease outbreaks. Overall, DL-IoT technologies significantly elevate data-driven intelligence in the healthcare sector, promoting precision, accessibility, security, and operational efficiency.

Patient Monitoring

Patient monitoring is essential for timely diagnosis, early complication detection, and overall patient safety particularly regarding chronic illnesses such as hypertension, diabetes, cardiovascular disorders, and respiratory conditions. However, within Nigeria’s resource-limited health facilities, manual monitoring methods are constrained by staff shortages, overcrowded hospitals, and limited access to continuous vital sign measurement. Manual monitoring often depends on periodic checks, which increases the possibility of missing critical

physiological changes and contributes to delayed interventions. As a result, the manual system achieved a relatively low performance rating of 40 points.

The adoption of DL-IoT healthcare systems introduces intelligent and automated remote monitoring capabilities. Wearable medical sensors collect patient data including heart rate, blood glucose, blood pressure, oxygen saturation, temperature, and ECG signals in real time. Deep learning models continuously analyze these data streams to detect abnormalities and trigger alerts when intervention is required. With this advantage, the DL-IoT monitoring approach scored 90 points, signifying a substantial advancement of more than 125% improvement over the manual approaches.

This continuous monitoring capability is particularly impactful for Nigerian rural communities where patients may live far from medical centers. Remote-care support enables healthcare access for home-based patients and reduces frequent hospital visits, which translates into decreased healthcare costs and reduced clinic congestion. By ensuring uninterrupted observation and timely response, DL-IoT patient monitoring systems improve the management of chronic illness, reduce emergency hospitalisations, and significantly enhance patient safety and quality of life.

Economic Impact

Healthcare affordability remains a major concern in Nigeria due to limited funding, high patient loads, and expensive reliance on manual labor-intensive processes. The manual healthcare system incurs continuous operational expenses associated with documentation, diagnostic delays, and extended patient hospital stays. These inefficiencies reflect in the high score of 80 for healthcare costs in the manual system, indicating that traditional methods create continuous financial burdens for both institutions and patients.

The DL-IoT healthcare model, however, introduces automation that reduces operational expenses in the long term. Automated diagnosis and smart monitoring limit the need for frequent clinical checkups, reduce hospital readmissions, and enable early disease intervention ultimately lowering treatment expenses. Additionally, faster decision-making improves patient throughput and resource utilization. These advantages contributed to a significantly lower economic cost score of 60 for the DL-IoT system. Despite its cost-saving benefits, the adoption of DL-IoT in Nigeria faces several initial financial barriers. Deployment requires investments in: advanced

computing infrastructure, IoT-enabled medical sensors and wearable devices, stable internet connectivity and power supply, personnel training on digital health tools and cybersecurity and data protection systems.

These startup costs are especially challenging for rural healthcare centers operating under constrained budgets. Nevertheless, when evaluated from a long-term sustainability perspective, DL-IoT offers measurable economic efficiency, reduces over-dependence on physical hospital visits, and provides scalable cost benefits as usage expands. Therefore, early-stage investment if supported by government subsidies and public-private partnerships can yield significant financial returns and broader national health improvements.

Scalability

The scalability of healthcare systems determines their ability to manage increasing patient populations and evolving medical demands. Nigeria's manual healthcare system is inherently limited in this regard due to inadequate infrastructure, shortage of skilled professionals, and reliance on static equipment. These constraints make expanding services costly and slow. The manual system scored 30 points on scalability, emphasizing its inability to efficiently support Nigeria's rapidly growing population and healthcare needs.

In contrast, the deep learning enabled IoT system demonstrates exceptional scalability. Its architecture allows flexible integration of additional devices, modules, and cloud-based applications without significant increases in operational complexity. For example: New patient devices can be added to the network seamlessly, Cloud storage supports expanding digital medical records and System capacity can grow without requiring major infrastructure upgrades.

With a performance score of 90 points, the DL-IoT system shows a 200% improvement over manual methods. This scalability is particularly beneficial in: Expanding telemedicine coverage in rural communities. Rapid deployment during infectious disease outbreaks. National-level health data analytics and population monitoring. Supporting nationwide digital health transformation initiatives. Additionally, scalable digital solutions enhance interoperability between hospitals, specialties, and public health institutions, enabling a unified and efficient healthcare delivery network across the country

Challenges of DL-IoT Adoption in Nigeria

Although DL-IoT healthcare systems demonstrate substantial performance advantages over manual approaches, their implementation in Nigeria faces major infrastructural, economic, technical, and sociocultural challenges that must be addressed before nationwide deployment can be achieved.

Limited Digital Infrastructure and Power Supply:

IoT systems rely heavily on stable broadband internet connectivity and uninterrupted electricity. However, many hospitals particularly in semi-urban and rural areas experience inconsistent power supply and slow network coverage. These limitations affect real-time data transmission and the reliability of automated healthcare services.

Without upgraded national digital infrastructure, the DL-IoT ecosystem cannot function at full capacity.

Deep learning platforms, wearable medical sensors, cloud storage systems, and secure network installations require significant investment. Public hospitals in Nigeria often operate on constrained budgets, making it difficult to afford initial implementation. While long-term benefits reduce operational expenses, the transition cost remains a major barrier to early adoption without government incentives, donor support, or private-sector partnerships.

Healthcare data is extremely sensitive and must be protected against cyber threats such as unauthorized access, ransomware attacks, and identity theft. Many Nigerian institutions lack strong cybersecurity frameworks and regulatory compliance protocols. Data governance policies including encryption standards, data retention guidelines, and privacy protection must be strengthened to ensure trust and legal compliance with digital health practices.

DL-IoT systems require personnel trained in data science, AI model deployment, sensor integration, and cloud administration. Nigeria faces a shortage of such specialists, exacerbated by continuous healthcare workforce migration to other countries. Without professional training programs, system maintenance and scalability will remain difficult, limiting sustainable adoption.

Cultural beliefs, low digital literacy, and limited knowledge about AI-assisted healthcare hinder acceptance of autonomous monitoring and diagnostics. Some patients may distrust technology-driven diagnoses or view wearable sensors as invasive. Awareness campaigns, community education, and culturally sensitive digital health policies are essential to improve public acceptance and utilization.

To enable large-scale deployment, the following strategies are recommended: Government investment in e-health infrastructure Cybersecurity standards and strong data protection policies Training programs for medical practitioners Public–private partnerships for IoT deployments Affordable local manufacturing of IoT devices

Conclusions

Deep learning–based Internet of Things systems significantly outperform manual healthcare systems in Nigeria across all examined metrics. They provide: faster disease detection, higher diagnostic accuracy, efficient patient data & monitoring, scalable and data-driven services. The transition to intelligent healthcare is essential for improving national health outcomes and supporting universal healthcare coverage in Nigeria.

Supplementary Material

Not applicable

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