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***Research paper***

# ML-Based Decision Support in Point-Of-Care Testing Devices: Revolutionising Rural Healthcare

**Venudhar Rao Hajari ***

*Independent Researcher Nagpur University, India*
**Corresponding author E-mail: haliconpublication@gmail.com*

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**Abstract**

Specialized diagnostic personnel and centralised laboratories are not available in most rural and underserved health-care settings. This implies that the devices are less accurate in delivering medical care, leading to delays. PoCT Devices Using Machine Learning (ML) Based Decision Support is a high-impact technology. Point-of-care diagnostics such as blood analysers, mobile microscopes, and disease test kits are designed to support community-level diagnostics by frontline health workers. With the integration of ML algorithms, these devices can analyze data in real time, identify patterns, and generate predictions. This leads to faster diagnosis, less human error, and personalized treatment. This paper discusses how to train ML models for low-power and offline environments. It looks at their capabilities in the rural environment and their ability to deliver the appropriate responses. Data privacy issues, model robustness, and field parameterisation are also discussed. The paper evaluates how ML-enabled PoCT devices can reduce the inequality in healthcare. Stand-alone ambulance solutions are a relatively low-cost and widely scalable service that can help grow medical capabilities in rural areas where they are otherwise missing.

***Keywords***: *Machine Learning; Point-of-Care Testing; Rural Healthcare; Portable Diagnostics; Decision Support Systems; Clinical AI.*

## 1. Introduction: Bridging The Rural Healthcare Gap Through AI

Still on the challenges and opportunities of healthcare in rural settings, PoCT devices play an important role in increasing the healthcare infrastructure in rural settings. The high speed and almost patient-like diagnostic outcomes cancel out all the time and logistical complications of the centralized diagnostic laboratories. This feature is essential in isolated areas where there is a low level of laboratory facilities, and tracking patients on a recurrent basis may be difficult [11] [12]. The simplest are the qualitative comparative essays, e.g., lateral transport versus malaria, HIV, where the results are binary (yes/no). More sophisticated ones are handheld haematology analysers, handheld ultrasound scanners, and mobile microscopes that can offer either a quantitative or imaging-based diagnosis. They offer information that cannot be easily interpreted by one who is not conversant with them; this is where the ML information comes in [13]. One of the issues that high-performance PoCT use in rural regions is that the equipment must be robust enough to resist the environment, including dust, humidity, high temperature, and unreliable power supply. They should also be dependable and user-friendly for low-literate and less educated people. It may also include user-friendly navigation and interpretation of outputs through colour coding, iconography, and easy language on the interface [14]. ML is able to eliminate the guesswork in this signal exchange. Algorithms can be hardened into the sensor and provide real-time, actionable results transparently that do not need human interpretation. The added advantage of this is that it enhances accuracy and minimizes diagnostic errors by the poorly trained community health workers [15].

A good case in point was an anaemia screening program in rural India battery-driven haemoglobin analyser unit. They are applied in community health screening of anemia among pregnant women. They can still be implemented in the case of higher-risk gravidities, even in facilities where there is no clinical supervision at the point-of-selection, and there are available ML-enhanced forms which automatically report low haemoglobin values to be referred to as such [16]. Besides diagnostics, PoCT instruments may become significant targets of larger health information systems. As long as it is possible to ensure their safety, they will be able to transmit anonymised diagnostics back to regional or national health IT systems. Information sharing of disease outbreak surveillance and drug-resistant pathogen surveillance was done using this real-time data [17]. In the offline world, a periodic synchronisation of data in the form of persistent or offline storage is possible. This will guarantee that even the rural diagnostic activities will provide national and global public health intelligence at the population level. Outlining these technical features of PoCT devices, we will provide a basis to discuss technological considerations and requirements peculiar to the implementation of ML models in the PoCT system in the following section.

## 2. Overview of Point-Of-Care Testing Devices in Rural Settings

Moving from the previously discussed challenges and opportunities for healthcare in rural areas, PoCT devices have a key role in boosting the healthcare structure in rural areas. The rapid, near-patient diagnostic results negate all the delays and logistical challenges of centralized diagnostic laboratories. This capability is critical in remote locations where laboratory infrastructure is low, and following patients on a recurring basis can be challenging [11] [12]. At the simplest level are qualitative comparative essays, such as lateral transport for malaria and HIV, with binary (yes/no) results. More advanced instruments include handheld haematology analysers, handheld ultrasound scanners, and mobile microscopes capable of quantitative or imaging-based diagnostics. These provide high-fidelity information that is hard to interpret if one is not familiar with them; this is where ML information becomes useful [13]. A major challenge for high-performance PoCT deployed in rural areas is that the measuring devices should withstand environments, such as dust, humidity, high temperature, and unstable power. They must also be reliable and easy to use for low-literate and minimally trained individuals. The interface could incorporate supportive features such as colour coding, icons, and simple language to facilitate navigation and interpretation of outputs [14]. ML can remove the guesswork from this signal exchange. Algorithms can become integrated into the sensor and transparently output actionable results in real-time that do not require human interpretation. This has the added benefit of improving accuracy while reducing diagnostic errors on the part of the minimally trained community health workers [15].

An excellent example of this was the battery-driven haemoglobin analyzer unit for an anaemia screening program in rural India. These are being used in community health camps for screening of anemia in pregnant women. Even in facilities lacking clinical supervision at the point-of-selection, where ML-enhanced forms that automatically flag low haemoglobin values for early referral are available, they may still be deployed for higher-risk gravidities [16]. In addition to diagnostics, PoCT instruments can become important endpoints in broader health information systems. If connectivity can be made safely, they will be able to send anonymised diagnostics back into regional or national health IT systems. This real-time data was used for information sharing for disease outbreak surveillance and drug-resistant pathogen monitoring [17]. In offline environments, data can be synchronised periodically through persistent or offline storage. This approach ensures that rural diagnostic activities also contribute to national and global public health intelligence at the population level. By describing these technical characteristics of PoCT devices, we will lay a foundation for discussing technological requirements and considerations specific to the integration of ML models into the PoCT system in the next section.

## 3. Machine Learning in Embedded Systems: Architectures and Constraints

In order to understand how PoCT devices have a practical relevance for rural healthcare, an analysis needs to be conducted of the technology that supports the applicable ML consolidation. As shown in Figure 1, these devices need to be able to do their job without extended assistance. This leads to the requirement for low-power, compact, and rugged embedded systems that are capable of computing data in situ subject to resource constraints [18][19]. PoCT devices are, unfortunately, mostly embedded systems, integrating microcontrollers or Systems-on-Chip (SoC), sensor interfaces, and a small amount of on-board memory, and occasionally specific AI accelerators. From the processing power and memory point of view, these platforms are small compared to the high-performance server-grade infrastructure. In addition to the need to fine-tune ML models, we must also ensure diagnostic accuracy remains uncompromised. There also exists a need for models to be computationally efficient [20].

Most ML-enabled PoCT instruments are based on a sensor -> compute -> output pipeline. Sensors (optical detectors, biochemical analysers, imaging modules, etc.) acquire information from the patient. This information is cleaned and pre-processed using DSP or additional enhancement techniques. The processed inputs are then passed to an embedded ML model that generates diagnostics such as classifications or risk scores. Results are presented via the associated intuitive user interface with colour-coded graph or therapy prompt elements for ease of understanding for these different levels of trained HCWs [21]. But one of the fundamental limiting factors has been memory. The problem is that PoCT devices do not have hundreds of megabytes; instead, a few megabytes or less, which cannot host software applications that demand hundreds of megabytes for deep learning models. These limitations lead to the use of model compression schemes (quantisation, pruning, knowledge distillation, etc.) where the goal is to achieve a smaller model size while maintaining most of the performance [22]. Another important topic that certainly cannot be overlooked is power consumption. Many of these imaging devices must be carried for extended periods; therefore, they must be battery-operated with no opportunity for recharging. Alternatively, advanced triggering mechanisms such as duty cycle mode (where the device components are only powered at the status change) and anomaly-based inference (where ML processing is only done when detected anomalies occur) can help save energy while extending the battery life [23]. Network connectivity impositions also determine the design. Further, real-time updates and complex processing are possible on cloud-based systems, while many rural areas are also not reachable due to the lack of stable mobile connections. Thus, PoCT devices need to be able to run inference offline. These updates may be provided through portable storage, visits from healthcare workers, or through delay-tolerant and satellite communication for sending important data [24].

A good example of such an application is to be found in portable tuberculosis diagnosis rigs used throughout rural Asia. Portable vans integrate digital X-ray systems and convolutional neural networks (CNN), which are trained for image capture, processing, and classification onboard. This enables full same-day diagnosis and treatment initiation without having to transfer large image volumes to remote servers [25]. Security and privacy also have to be built into the design of the device from the very beginning. In rural locations, the limited availability of devices often leads to shared usage among multiple users, thereby increasing the risk of unauthorized access to sensitive data. This underscores the need for protection mechanisms such as data encryption, secure boot, and user authentication. In addition to general data processing, all methods of data processing should be compliant with national regulatory and privacy requirements that should conserve the trust and integrity of data of patients [26]. As a result, ML and PoCT hardware and software design are considered a sensitive balance. It requires some operations without electricity, it should be easy to use, and it requires information management and protection, especially outside the city. Naturally, these have knock-on effects on trainable ML models we discuss in more detail below.

The workflow of embedding systems with ML, described in Figure 1, takes sensor data through TinyML preprocessing, lightweight models, and an inference engine to actuate. It also identifies the deployment pipeline since training to model compression and code generation is included, as well as indicates the key limitations such as memory, power, latency, model size, safety, and security that affect the on-device ML performance.

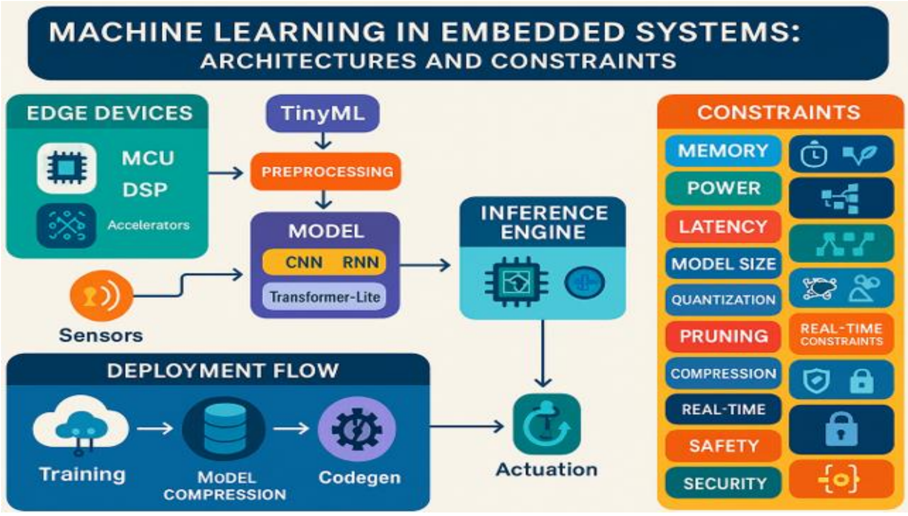


**Fig. 1:** ML In Embedded Systems for Edge Devices, Showing Data Flow from Sensors to Actuation, Deployment Steps, and Key Constraints Such as Memory, Power, Latency, and Security.

## 4. Types of ml Algorithms in PoCT Devices

When it comes to PoCT devices, which will be deployed in rural and resource-limited areas, one should look at the performance of the ML algorithms in a broader context that does not rely on the classic measures of accuracy. Supervised learning is the most used technique in which CNNs have been demonstrated to work well on image-intensive tasks such as malaria detection using mobile microscopy, and decision trees have been demonstrated to be useful in the classification of anaemia using structured blood parameters [29]. However, additional study of the literature indicates that certain inconsistencies occur in the trend of performance: whilst CNNs are dramatically better than decision trees in controlled or urban clinical situations, several studies, including [39], report that when the two models are used in rural conditions, the performance suffers significantly. The poor lighting, inconsistency in sample preparation, and the use of different devices, together with artefacts that vary according to the operator, make CNNs prone to misclassification since high-quality feature patterns are required. However, noisy, non-precise, or heterogeneous data may be more resistant to more complex models, e.g., decision trees, which are not so precise in an ideal environment, but can thus yield more predictable results when used in unpredictable rural environments. This discontinuity indicates a major issue, namely, trained models that are run on urban or laboratory-quality data are unlikely to extrapolate due to epidemiological differences, environmental bias, and demographic dissimilarity present in rural populations.

The reinforcement and the unsupervised learning methods complement each other in terms of being more advantageous, but also involve a list of side effects. The unsupervised clustering algorithms can be employed to detect new outbreak patterns in the environment where there are no such annotated data easily accessible or are expensive to access, and high-rank dimensionality-reduction methods, such as PCA, can help to make the analysis computationally viable on a low-power eTrER-based environment to filter the noise and retain significant signal contents [30]. Even though reinforcement learning is applicable to the optimization of the sequential decision-making process, which extends to the maternal health triage, this method should be applied with caution because uncontrolled exploration may lead to dangerous clinical procedures [31]. Trying to fill the exhausts in the individual paradigms, the recent research and practical application of the field are more predisposed to the hybrid models, which entail supervised, unsupervised, and RL components. As an example, hybrid systems, which fuse both unsupervised feature discovery to accomplish risk stratification and RL-based optimization of follow-up strategies in order to optimize both sensitivity of detection and operational efficiency, have been proposed [32]. It is also true that in East African clinics, the monitored neural networks, along with unsupervised clustering techniques, have been found to perform better compared to the ECG monitoring system in the detection of arrhythmia and the detection of exotic conditions when it is applied to monitor and check supervised neural networks [33]. These applications imply that hybrid architectures will be more adaptable, resilient, and diagnostic relevant to rural health settings. Table 1 summarizes these observations by trying to compare the types of algorithms according to the needs of data, the needs and strengths of computing, and the actual use in rural areas.

**Table 1:** Comparison of ML Algorithm Types for PoCT Devices in Rural Healthcare

| Algorithm Type | Data Requirement | Computational Load | Robustness to Noisy Data | Example Rural Use Case | Strengths | Limitations |
|---|---|---|---|---|---|---|
| Supervised Learning | High (labelled) | Medium–High | Moderate | Malaria detection via portable microscopy | High accuracy when trained on relevant datasets | Requires large annotated datasets |
| Unsupervised Learning | Low (unlabelled) | Low–Medium | High | Clustering patients by symptom patterns | Useful for outbreak detection and pattern discovery | Lower direct diagnostic accuracy |
| Reinforcement Learning | Medium (iterative feedback) | Medium | Variable | Adaptive maternal health screening recommendations | Optimises decision pathways | Risk of unsafe exploration in medical contexts |
| Hybrid Models | Variable | Medium–High | High | Integrated HIV screening and risk stratification | Combines the strengths of multiple paradigms | Higher design complexity and resource demand |

## 5. USE Cases of ML-Enabled PoCT Devices

The dynamics of ML algorithms in PoCT devices can ultimately be illustrated through a range of use cases. The examples presented demonstrate how the integration of AI enhances diagnostic capabilities on mobile platforms, while also addressing critical information gaps left by traditional laboratory infrastructure. Infectious disease surveillance, chronic disease surveillance, and maternal & neonatal health monitoring are the main areas of application [34] [35].

Infectious disease care is one of the vanguard fields that gained tremendous benefits from ML-enabled PoCT. Smartphone-based microscopy can be used to diagnose malaria parasites in stained blood slides as accurately as expert microscopists with the aid of convolutional neural networks. This is especially relevant in rural sub-Saharan Africa and South-East Asia, where there are few or no competent laboratory scientists available. Also, portable X-ray machines with deep learning algorithms allow point-of-care screening for tuberculosis by recognising pulmonary abnormalities without the need for a centralised radiology facility [36]. Improved interpretation of lateral flow tests during HIV screening is one such example. In poorly lit conditions, it is easy to miss the appearance of faint test lines. However, image recognition models have been shown to improve the accuracy of test interpretation, even under such challenging conditions commonly found in rural medical facilities [37]. These tools can be used to identify earlier, to add layers of confidence, and to reduce the burden of interpretation on humans.

ML-based PoCT is also changing the way we manage chronic diseases in rural areas. There is limited access to laboratory testing for blood glucose and HbA1c, and whatever is available is expensive and does not support diabetes management. ML-powered handheld analysers can analyse biochemical data in real-time, identify mycobacteria, and predict glycemic patterns and intervene before things go wrong. On the other side, wearable ECG monitors with ML models built upon will detect arrhythmias and symptoms of CV disease locally for early referrals before serious cardiac events [38]. In the fields of maternal and neonatal healthcare, ML-supported PoCT devices have demonstrated the capability of saving lives. Touchscreen ultrasound with ML algorithms embedded can identify complications such as placenta previa or fetal growth restriction even when no trained sonographer is available. Haemoglobin analysers are a quick way to screen for anaemia in high-risk pregnancies that can be addressed by referral. For neonates, the ML-enhanced bilirubin test can easily predict the risk of having severe jaundice, and early treatment with phototherapy can be administered to avoid neurological impairment [39].

Produced field implementations have emphasised scalability and flexibility. In rural India, for instance, ML-powered haemoglobin meters, glucometers, and mobile data platforms integrated with community health programs are being used to generate individual patient profiles. These profiles provide valuable insights that guide the work of community health workers. In East Africa, ML-augmented PoCT-enabled mobile health vans deliver care for HIV, tuberculosis, and malaria to remote villages. For many residents, these vans often represent the first point of medical access [40]. These various use cases show ML-driven PoCT devices are not restricted to single-disease diagnostic work. Rather, they can be a methodology that supports multi-disease platforms, which can be adapted to different rural healthcare problems. For such systems to effectively serve these purposes, intelligent devices are required with designs appropriate to low-resource environments; this requirement is examined in the subsequent section.

## 6. Design Considerations for Rural Deployment

The success of ML-enabled PoCT devices in rural healthcare depends not only on diagnostic accuracy but also on how well they meet the environmental and operational challenges of low-resource settings (as shown in Figure 2). Devices must be resilient, accessible, and sustainable, capable of operating reliably despite poor infrastructure and harsh conditions [41] [14] [18]. Power efficiency is a top priority, as many rural clinics lack consistent electricity. Devices must conserve energy through hardware optimisation, model quantisation, and duty cycling, which activates components only when needed [42] [23].

An intuitive user interface is also essential. Many rural health workers have limited training, so simple visual cues like traffic-light colour coding help reduce errors. ML models should not only analyse data but also present clear, actionable results for easy decision-making [43] [21]. Offline functionality is critical. Devices must operate independently of internet access, using on-device ML, secure local storage, and delayed data syncing. For example, mobile TB screening units with embedded CNNs can run diagnostics offline and upload results later [44] [25]. Mobile health (mHealth) integration adds further value. PoCT tools with Bluetooth or low-energy transfer can update patient records and enable follow-up care via mobile apps, streamlining workflows for community health workers [45] [46]. Durability is a critical requirement for these devices. They must withstand dust, moisture, extreme temperatures, and frequent rough handling. Incorporating features such as rugged casings and sealed components similar to those in haemoglobin analysers used in rural India helps extend their operational lifespan [47] [48]. Lastly, cost-effectiveness matters. Modular systems that support upgrades, such as adding new ML models or sensors, help extend usability and improve return on investment [8] [40]. By addressing these core design principles, efficiency, usability, offline operation, mHealth integration, durability, and affordability, ML-based PoCT devices can deliver sustainable, high-impact care in rural settings. The next section explores how their clinical and operational performance is evaluated in both lab and field contexts.

The major design considerations in the implementation of PoCT in rural settings, as illustrated by Figure 2, are the factors of low infrastructural connectivity, poor weather, extreme power and energy provision, and issues of maintenance and servicing.

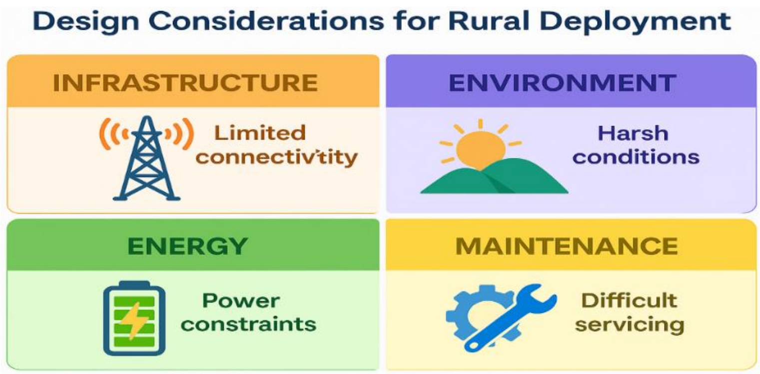


**Fig. 2:** Key Design Considerations for Rural Deployment, Highlighting Infrastructure Limitations, Environmental Challenges, Energy Constraints, and Maintenance Difficulties.

## 7. Performance Evaluation Metrics

To be useful for rural healthcare, ML-driven PoCT devices need to work reliably in real-world settings (rather than in controlled laboratory settings). Reliability of a diagnostic is not just determined by the diagnostic accuracy but also by its operational reliability and ease of use in limited resources [5] [11] [49]. One of the balance requirements of a clinical diagnostic test is diagnostic accuracy-the sensitivity and specificity combined to represent a particularly accurate test. For diseases such as tuberculosis and malaria, for which only the positive results are of interest, the sensitivity will be high. Negative predictive value (NPV), often discussed alongside specificity, highlights an important limitation: the inability to detect a condition does not necessarily imply that treatment is unnecessary. Drawing parallels, metrics such as Medication Daily WMSI [50], as well as PPV and NPV, support the interpretation of diagnostic results. These measures help determine whether the reliability of a test is sufficient to forego confirmatory testing, an essential consideration in resource-limited settings [29] [50]. Robustness is equally vital. Instrumentation must perform in the face of poor lighting conditions, variable sample quality, and patient heterogeneity. One highly useful technique for adapting algorithms that are developed under controlled conditions to the vagaries of the real world is robustness testing [39] [47]. Another important number is time-to-result. Rapid testing, for same-day treatment, to help increase retention (for example, ML-based HIV rapid tests may be able to provide a result within less than 60 seconds for immediate counselling and referral [37] [48]. Another performance in the field factor is usability. Reduced propensity for operator error is through legibility of graphical displays, such as at traffic lights-Usability between 1 with standardized tools (such as the System Usability Scale [SUS]) is generally very high with intuitive PoCT devices, even with (only) low training of operators [15] [41]. Field validation has exhibited a loss of performance, which is not seen with laboratory performance testing. For example, there were high laboratory accuracies (96.3+2.5%) when mobile ML-enabled X-ray TB reader units were operated, but there was a need for changes to mobile implementation that were identified as a result of IQ (image quality) issues. Not only that, but completely new training and hardware vendors had to be engaged to bring the accuracy back [25][46]. Cost effectiveness is an ever increasingly important concept. Correct diagnosis cost or DALY (learning years) averted are indicators employed for making the investment decision. Adding lifetime value to rural health systems can be achieved through sliding-scale upgrades that do not require hardware replacement [8] [50]. However, robust evaluation paradigms addressing clinical accuracy, reliability, speed, usability, and economic viability are essential for effective deployment. In addition, these tools require supportive regulatory, infrastructural, and cultural frameworks to ensure their successful adoption and use.
The section then continues to address some of the more holistic issues of ethics and various barriers to integration within rural healthcare. Clinical, operational, and economic performance results from trials in the field are summarised in a matrix of key performance metrics shown below.

**Table 2:** Integrated Performance Evaluation Framework for ML-Enabled PoCT Devices

| Metric Category | Specific Metric | Measurement Method | Rural Deployment Relevance | Example Threshold for Acceptance |
|---|---|---|---|---|
| Clinical Accuracy | Sensitivity & Specificity | Field trials with diverse sample sets | Ensures correct identification of true positives/negatives | ≥90% sensitivity & ≥85% specificity |
| Robustness | Environmental Tolerance | Stress testing under varied temperature/humidity conditions | Reliability under harsh rural conditions | Stable output at ±10°C deviation |
| Speed | Time-to-Result | Measured from the sample input to the output | Enables same-visit diagnosis and treatment | ≤5 minutes per test |
| Usability | System Usability Scale (SUS) | Operator surveys across skill levels | Reduces training burden and errors | SUS ≥80 |
| Economic Impact | Cost per Correct Diagnosis | Health economic analysis | Supports cost-effectiveness in low-resource settings | <5 per diagnosis |

## 8. Challenges and Ethical Considerations

Although the potential benefits of the ML-based PoCT devices in clinical practice and their cost-effectiveness may be promising, the issue of their incorporation into the healthcare system of the rural environment cannot be seen as anything short of technical precision. This problem of data privacy, flexibility of the algorithms, and social and cultural acceptability ought to be resolved to bring out the long-term sustainability [6] [18] [26]. The reason is that the confidentiality of the information is a sensitive issue, as PoCT gadgets are linked to mHealth and centralised servers. Intrusion is a factor that is likely to increase when there is no cybersecurity solutions in the countryside. Such viable measures as the encryption of static data with AES-256 key, the use of TLS 1.3 protocol during the transfer of confidential data, and role-based access control (RBAC) should be implemented to ensure that patient data is secured. Another form of structured protection is also offered by compliance with the developed regulatory frameworks, including the principles of data minimization of GDPR and the safeguards of HIPAA for protected health information. The use of anonymisation methods (e.g., k-anonymity, differential privacy) and trust can be dissuaded by discouraging re-identification of patient records, and trust in the community will be enhanced [24] [26].
Elasticity of ML algorithms is another issue of concern. Part of the models are conditioned primarily on the city data, and hence do not have the capability to extrapolate to individuals in the rural regions, and possess a varied health distribution or a disparate environment. Transfer learning, local fine-tuning, and on-device retraining can decrease this mismatch at the cost of computational resources and validation tests, which are limited in low-resource conditions [39] [47]. The other similar problem is the model drift, in which the algorithm will deteriorate as time progresses because the trends of disease, changes in behavior, or the mutation of pathogens will change. Examples of activities that should be incorporated in the proactive management of drift include the generation of periodic retraining programs, data-drift detection components, and federated learning to refresh models without the need to access sensitive information about the patient - some of them are presented in computing journals like [22] and [29]. In the absence of such, there might be a risk of misidentifying an old model and system inefficiency.
The culture should also be assimilated, and the aspect of human factor inclusion in the care processes should be embraced. Most of the rural populations put a lot of emphasis on human interaction, thus any automated decisions made should be contextualized and be supplemented by health workers at the community level so as to appear credible. The individuals in charge of the community are able to influence the degree of attitude to new technologies, and their approval can be used to accelerate the process of acceptance [15] [41]. Combined with social conditions, systemic logistical issues, including insufficient rates of consumables, the absence of spares, and the absence of technical support, can undermine the equipment's stability. Also, local maintenance ecosystems should exist even in a modular design to be effective [16] [40]. An example of the studies on the ML-enabled chest X-ray tuberculosis screening in remote clinics can serve as an explanation

of such concerns: despite the first positive results, the implementation of the models is also characterized by the necessity to change the models on a regular basis, the unavailability of specialists, and patient reluctance. Pragmatically, the first outcomes were required to be manually checked so as to accord credibility and confidence to the clinicians [25] [46].

Finally, it should be emphasized that all of these issues can be resolved only by the collaboration of technical protection, adherence to the regulations, development of the local capacity, and community participation. It is the only approach that can be scaled even to rural area on a sustainable level, but this will involve the implementation of the PoCT devices, which are technological.

## 9. Future Directions: Towards Intelligent Community Health Systems

Overcoming technical and support challenges alone is not sufficient to guarantee the long-term sustainable use of PoCT devices equipped with ML in rural health contexts. A broader vision involves integrating these tools into intelligent, data-driven community health systems that enable coordinated care and real-time disease surveillance [7] [17] [50]. One of the key opportunities currently is the concept of diagnostic networks in which PoCT devices can function as nodes in networks for secure exchange of anonymised data between regional and national data systems. This makes it possible to track epidemics as they occur, giving early warning of epidemics. For example, deployment of a network of ML-enhanced malaria microscope centres could help activate prompt mosquito control and treatment campaigns [9] [46]. Therefore, novel technologies such as Edge computing and federated learning are of great importance for local training that do not jeopardise data privacy. In federated learning, the devices train on their data locally, and then only the updates get sent to the server (not the actual data). The latter not only can conform to the scaling of a resource with limited bandwidth, but also can adapt to new and emerging challenges without high-bandwidth Internet access [50] [24].

A fairly new and emerging trend is the multimodal diagnostic platform. Instead of having separate tools for diseases like HIV, malaria, or anaemia, there can be just one ML-powered device that can have various tests and measure all results together in a holistic way. This results in decreased diagnostic availability, reduced hardware costs, and easier maintenance [8] [40]. On the other hand, the expanding tidal wave of predictive and preventive analytics continues to drive the opportunity for PoCT. For example, ML-based glucose monitoring devices that anticipate the onset of hypoglycemia (low blood sugar), or wearables with embedded algorithms that signal an early sign of heart failure [48][49] are intended to trigger early and effective therapeutic intervention. One can develop these local skills and also bring the people to unlock the potential. Health workers must be trained in the use and interpretation of device outputs, and confidence must be built through culturally appropriate communication between the health system and the communities being served. Technical aids, the provision chain, and process form: in addition to assisting, proposals between all traders, governments, and NGOs suggest that technical assistance, maintenance, and services are also important for processes and demonstration of techniques [15] [41]. Many of these concepts are already being put into practice. In East Africa, healthcare solutions are delivered through ML-powered PoCT devices connected to enterprise dashboards in mobile clinics. Similarly, in India, federated learning is being tested in maternal health pilots within rural health programs, enabling offline models to be calibrated locally while still maintaining privacy protections [16] [50]. Finally, machine learning-based PoCT (mL-PoCT) solutions are rapidly emerging as the core for interventions needed to achieve the levels of scale, proactiveness, and equity that rural health systems already demand. To achieve such a goal, they need the perfect triangle of innovation, regulation, and trust. Finally, this paper will take a step forward to synthesise these insights and seal the fate of ML-based diagnostics as an instrument in the toolbox for retuning the world's equation of equality.

## 10. Conclusion: Reimagining Diagnostic Equity Through ml

Integrated PoCT devices that utilise machine learning techniques represent a step forward for the future of standard-of-care PoCT delivery to underserved and rural communities. Further, portability, speed, and embedded intelligence are calibrated at the intersection of old mystical barriers to equity in healthcare (such as absent laboratory infrastructure, understaffed personnel, and delayed diagnostics), which have worn the conspicuous badge of inequity from time immemorial. In this paper, for PoCT, the technological platform of ML-enabled PoCT systems (embedded systems, limits, algorithm types, and applications) has been summarised. For both chronic diseases (such as maternal health and cardiovascular disease) and infectious diseases (such as malaria, HIV, and tuberculosis), the devices could deliver diagnostic performance that is almost as good as centralised testing platforms located in hospitals, at the point of care in resource-constrained environments. Features like the power usage, autonomy capabilities, simple interfaces, and rugged design characterise living systems, and are not optional accessories to the product but must be hard-wired into the mission to succeed. Performance evaluation of the analyses is demonstrating favourable results as regards clinical sensitivity, specificity, ease of use, and overall cost-effectiveness. However, their practice comes with inherited challenges linked to data privacy risks, model drift, supply chain constraints, and cultural acceptance, all of which need to be addressed for long-term deployment within rural health systems. Overall, the value-added potential of these existing sensor technologies for transformation has more to do with the fact that, in the relatively distant future, they should no longer be one-off tools, but networks of interconnected nodes that can express functionality as part of an intelligent system in community health care. Sensors, artificial intelligence, and computer vision will enable those systems to not only diagnose but also predict health risks, as well as the corresponding measures. As healthcare is set to slowly shift from reactive to proactive practices in rural communities, ML-driven PoCT devices paired with robust complementary local capacity building and community trust can be a tremendous tool in the right direction. Ultimately, they will be judged, in part, based on how well these innovations reduce the disparity in diagnosis between urban and rural areas, and at any point when that gap is no longer widening, but rather slowly reducing. When developed for areas with limited resources (not just adaptation of an ML implementation), ML-powered PoCT instruments become more than a technical solution. Communities are becoming social justice resources, not bound to geography, or fuel sources-but by inclusion and by smart health services.

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