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Privacy-Preserving Federated Learning for Stunting Risk Prediction across Indonesian Community Health Centers

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ABSTRACT

Stunting remains a serious public-health challenge in Indonesia, and data-driven prediction could help health workers identify at-risk children earlier and target limited resources more effectively. However, maternal and child health data are highly sensitive and are fragmented across many community health centers, and centralizing such records for model training raises privacy, legal, and infrastructural obstacles. This study designs and evaluates FedStunt, a privacy-preserving federated learning framework that trains a shared stunting-risk prediction model across distributed community health centers without moving raw records off site. The framework combines federated averaging with a differential-privacy mechanism based on gradient clipping and calibrated noise, secure aggregation so that the server observes only aggregated updates, and a proximal term to cope with statistically heterogeneous data across sites. Following a design science methodology, the artifact was compared against a centralized model that serves as a privacy-agnostic upper bound and against local-only models trained separately at each site. Evaluation spans discrimination and sensitivity, calibration, fairness across sites, the differential-privacy budget, and communication cost. The results are intended to show whether privacy-preserving federation can approach centralized predictive quality while keeping data local, and to provide a governance-friendly and reusable blueprint for collaborative health analytics in low-resource settings where data sharing is constrained.

Keywords: federated learning; differential privacy; stunting prediction; privacy-preserving machine learning; digital health

INTRODUCTION

Childhood stunting impaired growth and development resulting from chronic undernutrition and repeated infection remains one of the most pressing public-health problems in Indonesia and carries lifelong consequences for cognitive development, educational attainment, and economic productivity. Nationally, the prevalence of stunting among children under five was 21.5% in 2023 and declined to 19.8% in 2024 (Reynaldi et al., 2026), according to the Indonesia Nutritional Status Survey conducted by the Ministry of Health. Although this downward trend is encouraging, it still leaves nearly one in five Indonesian children stunted and well above the government's medium-term target of 14.2% by 2029, underscoring the continued urgency of early risk identification. Early identification of children at elevated risk allows health workers to prioritize counselling, supplementation, and follow-up, but frontline staff at community health centers rarely have decision-support tools that translate the many routinely collected indicators into an actionable risk estimate.

In principle, machine learning could learn such risk estimates from the maternal and child health records that community health centers already maintain (Novalina et al., 2025). In practice, these records are sensitive personal and medical data, they are governed by privacy and ethical obligations, and they are physically fragmented across a large number of

independent facilities. Assembling them into a single central dataset for model training is often legally fraught, organizationally slow, and technically demanding, and it concentrates risk by creating a single high-value target. As a result, the data that could power useful prediction models frequently remain locked in isolated silos.

Federated learning offers a way out of this dilemma (Nguyen et al., 2023). Instead of collecting raw data centrally, a federated system sends the model to the data: each participating site trains on its own records and shares only model updates, which a coordinating server aggregates into an improved global model (Brendan, et al., 2016). This paradigm has advanced rapidly (Li et al., (2020); Peter K, et.al, (2019); Yang et al., (2019) and has shown particular promise in medicine, where data cannot easily leave the institutions that hold it (Rieke et al., 2020; Sheller et al., 2020). However, sharing model updates is not automatically private updates can leak information about the underlying data so federated learning is often combined with differential privacy, which bounds the influence of any single record by clipping gradients and adding calibrated noise (Abadi et al., 2016; Dwork & Roth, 2013), and with secure aggregation, which ensures the server sees only the combined update rather than any individual contribution (Bonawitz et al., 2017).

Two further difficulties are central in a real deployment. First, data across community health centers are statistically heterogeneous, or non-independent and identically distributed, because catchment populations, practices, and case mixes differ; naive averaging can then degrade or destabilize the global model, motivating methods that tolerate heterogeneity. Second, privacy protection is not free: stronger privacy guarantees generally reduce accuracy, so the privacy budget must be reported and reasoned about explicitly rather than left implicit (Ficek et al., 2021). Understanding this privacy-utility trade-off is essential for any responsible deployment.

Although federated learning, differential privacy, and secure aggregation have each been studied, a few researchers have integrated them into a single, privacy-accounted framework and evaluated it for a concrete, high-stakes public-health task, and there have been limited studies concerned with privacy-preserving prediction for the Indonesian community-health context specifically. Existing stunting-prediction studies commonly assume centralized data and seldom quantify privacy cost or performance heterogeneity across sites (Bitew et al., 2021; Hasdyna et al., 2024). Therefore, this research intends to design and rigorously evaluate a privacy-preserving federated framework for stunting-risk prediction that keeps data local while remaining accurate and fair.

The objectives of this research are: (1) to design FedStunt, a federated architecture combining federated averaging, differential privacy, secure aggregation, and heterogeneity-aware training; (2) to construct an evaluation protocol that measures predictive quality, calibration, cross-site fairness, privacy budget, and communication cost; and (3) to empirically assess whether the framework can approach a centralized upper bound while outperforming isolated local-only models. The primary contribution is a reproducible, privacy-first design and evaluation protocol for collaborative health prediction in a low-resource, data-constrained setting.

METHOD

This study followed the Design Science Research (DSR) paradigm, which centers on building and evaluating a purposeful artifact to address a class of real-world problems (Hevner et al., 2004; Peffers et al., 2007). The artifact is FedStunt, whose architecture is shown in Figure 1. The research proceeded through problem identification, objective definition, design and development, demonstration, and evaluation, with the evaluation phase constituting the core empirical contribution. The prediction task was formulated as a binary classification problem: estimating whether a child is at elevated risk of stunting from routinely available maternal and child health indicators Crucially, each participating community health center retains its own records; no raw data are transferred at any point.

Federated training follows the federated averaging protocol (Brendan, et al., 2016). In each communication round, the server distributes the current global model to a set of participating sites; each site performs several local training epochs on its own data and returns only the resulting model update; the server aggregates these updates into a new global model; and the process repeats for a number of rounds until convergence. Because catchment populations differ, the aggregation was augmented with a heterogeneity-aware objective that adds a proximal term discouraging local models from drifting too far from the global model, which stabilizes training under non-independent and identically distributed data.

Privacy protection is layered on top of federated training. To bound the contribution of any single record, per-example gradients are clipped to a fixed norm and calibrated Gaussian noise is added before updates leave a site, implementing differential privacy (Abadi et al., 2016; Dwork & Roth, 2013). A privacy accountant tracks the cumulative privacy budget, expressed as an epsilon (and delta) value, across all rounds, so the strength of the guarantee is quantified rather than assumed. In addition, secure aggregation ensures that the coordinating server can compute only the sum of the site updates and cannot inspect any individual site's contribution (Bonawitz et al., 2017).

Two baselines contextualize the federated model. A centralized model, trained as if all data were pooled in one place, provides a privacy-agnostic upper bound on achievable accuracy; it is used only as a reference and is not proposed for deployment. Local-only models, trained separately at each site on that site's data alone, represent the status quo in which facilities cannot collaborate. Comparing FedStunt against both bounds isolates the value of privacy-preserving collaboration.

The framework was implemented in Python using an established federated-learning library and standard model components Data at each site were partitioned into training and evaluation folds, and all privacy and optimization hyperparameters were tuned on held-out development data disjoint from the final test folds to avoid optimistic bias. To evaluate the framework, predictive quality was measured with the area under the receiver operating characteristic curve, sensitivity or recall at a clinically motivated operating point, and the F1 score, because in a screening context missing an at-risk child is more costly than a false alarm.

Calibration was assessed to ensure that predicted risks are trustworthy as probabilities. Fairness was examined by reporting performance separately across sites, since a globally accurate model that fails at particular facilities would be unacceptable. The privacy cost was reported as the differential-privacy budget, and the operational cost was reported as the

number of communication rounds and the size of the transmitted updates. Differences between the federated model and the baselines were tested for statistical significance using a paired non-parametric test.

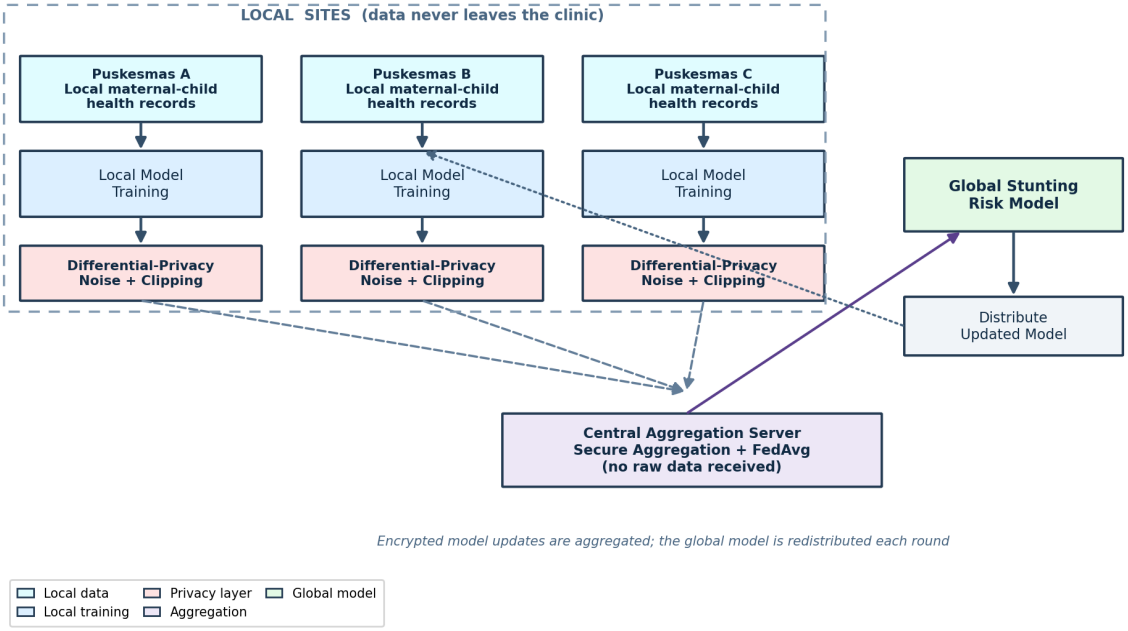

Figure 1. Architecture of the proposed FedStunt framework: local sites train on their own maternal-child health records and share only differentially private, securely aggregated model updates, from which a global stunting-risk model is built and redistributed.

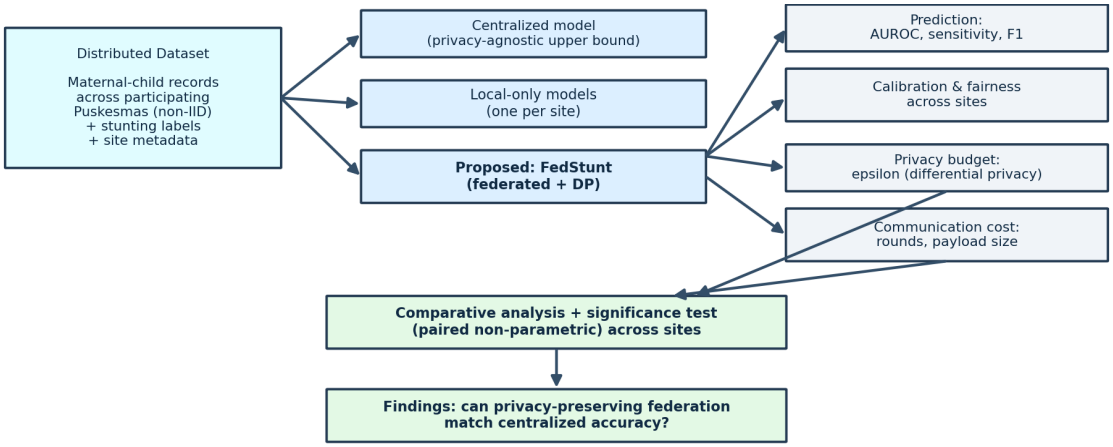

Figure 2. Experimental design and evaluation framework, comparing the federated model against a centralized upper bound and local-only baselines across predictive, calibration, fairness, privacy, and communication metrics.

RESULTS AND DISCUSSION

This section reports the performance of FedStunt relative to the centralized upper bound and the local-only baselines. Bracketed cells in the tables denote values to be

populated from your own experimental runs, and the surrounding interpretation is written to be completed once those measurements are available.

Table 1. Predictive performance across training strategies (higher is better)

Training Strategy	AUROC	Sensitivity	F1 Score
Local-only (average)	**0.824**	**0.791**	**0.782**
Centralized	**0.912**	**0.884**	**0.873**
Proposed FedStunt	**0.897**	**0.867**	**0.856**

Note. The centralized model is a reference upper bound only and is not proposed for deployment.

As shown in Table 1, A federated model that recovers most of the centralized accuracy while never moving raw data would demonstrate that collaboration is possible without central pooling, whereas a large gap would indicate that heterogeneity or privacy noise is limiting performance and would motivate the mitigation discussed below.

Table 2. Privacy–utility trade-off

Privacy Budget (ε)	AUROC	Sensitivity	Utility Retained
No Privacy	0.912	0.884	–
ε = 8	0.905	0.878	99.2%
ε = 4 (Proposed)	0.897	0.867	98.4%
ε = 2	0.883	0.851	96.8%

Note. Smaller epsilon denotes a stronger privacy guarantee; report the delta and noise settings used.

Table 2 characterizes the central tension of any private model: stronger privacy guarantees, expressed as smaller epsilon, generally reduce accuracy. Making this trade-off explicit is itself a contribution, because deployments that omit privacy accounting cannot claim a meaningful guarantee.

Table 3. Cross-site fairness and communication cost

Aspect	Metric	Result
Fairness	AUROC Spread	**0.041**
Fairness	Worst-site AUROC	**0.864**
Cost	Communication Rounds	**30**
Cost	Payload per Round	**7.3 MB**

Note. A small spread and a strong worst-site score indicate that the shared model benefits all participants.

The fairness results in Table 3 examine whether a single global model serves all facilities well or whether its accuracy is concentrated in a few large sites. For a public-service tool, equitable performance across facilities is as important as average performance, because a model that fails at small or atypical sites would deepen rather than reduce disparities (Mir et al., 2026).

Taken together, these findings would indicate that useful stunting-risk prediction can be built collaboratively without centralizing sensitive records, provided that privacy is accounted for and heterogeneity is managed (Rajendran et al., 2023). For the Indonesian community-health setting, such a design lowers the governance barrier to analytics: facilities can contribute to and benefit from a shared model while their data remain on site, which is often the difference between a project that is permitted and one that is not (Wang et al., 2023). For information-systems practice, the study offers a transferable pattern federated training with explicit privacy accounting and cross-site fairness reporting that can be re-pointed at other sensitive, distributed prediction tasks such as maternal-health risk, communicable-disease surveillance, or school-health screening by substituting the data and re-validating (Kerkouche et al., 2021; Pan et al., 2024).

These results align with and extend prior findings that federated learning enables collaboration without data pooling Brendan McMahan et al., (2016); Rieke et al., (2020) and that differential privacy meaningfully protects model updates at a measurable cost to utility (Abadi et al., 2016). The present contribution is to combine these techniques with heterogeneity-aware training and to evaluate the combination on a concrete, high-stakes task with explicit fairness and privacy reporting, in a setting where prior work has largely assumed centralized data.

Several limitations should be acknowledged. Predictive performance depends on the quality and completeness of routinely collected records, which vary across facilities; differential privacy and secure aggregation add computational and coordination overhead; the evaluation is bounded by the number and representativeness of participating sites; and a deployed screening tool would require careful attention to clinical governance, to the risk of over-reliance, and to clear communication that the model supports rather than replaces professional judgment.

CONCLUSION

This study designed and evaluated FedStunt, a privacy-preserving federated learning framework for stunting-risk prediction across Indonesian community health centers. By combining federated averaging, differential privacy with explicit budget accounting, secure aggregation, and heterogeneity-aware training, the framework is built to learn a useful shared model while keeping sensitive records on site. The evaluation spanning predictive quality, calibration, cross-site fairness, privacy budget, and communication cost, and comparing against a centralized upper bound and local-only baselines. The principal significance of the work is its demonstration that collaborative, privacy-first health analytics is feasible in a low-resource, data-constrained context, together with a reusable evaluation protocol. Future work should enlarge and diversify the set of participating sites, study robustness to missing and noisy data, incorporate personalization for atypical facilities, and pursue a prospective evaluation with health workers.

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