Self‑Reliant, Ultra‑Lightweight (≈48KB), Ultra‑Low‑Cost AI for Refugee Children and WomenToField Operations / Concerned OfficialsFromGyu‑min Jeon [ This document is a personal proposal and carries no legal obligations. ]SubjectRationale and Request for a Self‑Reliant, Ultra‑Lightweight (≈48KB), Ultra‑Low‑Cost AI for Refugee Children & WomenDate2025‑08‑19 (KST)

Your Excellency,

1) One‑Glance Summary of the Ultra‑Lightweight AI.We begin by preparingbaseline data—past incidents of camp violence, signs of psychological tension, child/women’s rights violations, and food distribution issues. No personal data is stored: only non‑identifiable numeric indicators such as time, location zone, noise level, crowd density, and help‑request button activity.

When a new signal arrives, the AI compares it with past data to ask, “Which previous cases are most similar?” (this isk‑NN). When field staff confirm or dismiss an alert, the AIimmediately adjustsits internal weights (this isRLS, online learning). In short, it evolves through a cycle ofbaseline → field feedback → tailored detector. With preloaded risk data it starts useful on day one, and then adapts in real time.

Crucially, refugees or NGOs can directly modify the data: this is anopen, self‑sustainingAI that can be locally maintained. The same≈48KBengine that powers our demo card runs entirely offline in a browser—no server or cloud calls—and shows the rationale for its estimates.

2) What We Have Built So Far (plain language).This is not a massive deep‑learning model, but a tiny decision engine that runs in a phone browser. It turns country/camp data into small feature vectors, finds similar past cases (k‑NN) to make an initial estimate, and thenself‑corrects quicklywith field feedback (RLS). Even with only a few dozen KB of memory, it transparently answers: “How close is this case to safe or unsafe?”

3) Why this reframes naturally to refugee protection.The current demo is a “country safety ticker,” but swapping the data turns the same engine into acamp risk signal estimator. Replace country metrics with camp‑level signals—time of day; block/tent zone; light/noise/crowding; help‑request texts; food queue length; security call logs—then encode them as small numeric vectors. k‑NN finds similar history; RLS rapidly adapts using true/false‑alarm feedback.

Offline & low‑power:runs entirely on site with solar + low‑cost devices (Raspberry Pi / budget Android), continuing detect→alert even if communications fail.Explainability:the card shows similar cases and top features so leaders, NGOs, and protection officers can audit the reasoning.

4) Theory in brief.k‑NN: compare with thekmost similar past signals and average their outcomes (e.g., “At night in Zone X with high noise and crowding, conflicts followed”).RLS: when staff feedback arrives, update weights in a few calculations—fast adaptation at KB scale.Blending: combine k‑NN and RLS to avoid bias/overfitting (the code’sblend()).

5) What the baseline data stores (non‑identifiable).Timestamp; zone ID (grid/label); signal summary (noise RMS, crowding, light change, movement); event label (argument, violence sign, GBV request, child‑missing alert, medical emergency, fire hazard, etc.); and outcome (field confirmation = true/false alarm).Human‑in‑the‑loop:protection staff finalize labels; their decisions update RLS so each camp localizes over time.Compliance:no face/voice ID; coarse zone‑level location only; strict minimization & purpose limitation; on‑site processing; encrypted, auditable logs.

6) Field scenario.Sensors/devices produce small feature sets every 1–10 seconds → the browser/app engine estimates risk instantly. If thresholds are exceeded, the card shows an alert (vibration/sound) and pushes to staff devices on the local network. Staff confirm true/false alarms → immediate RLS update → better, site‑tailored performance next time. Feedback loops help the model adapt to cultural/contextual nuances; alerts can be prioritized (e.g., medical emergencies first); aggregated history reveals structural issues like repeated stress in a particular block.

6‑B) Why now — urgency & context.Field reports from multiple regions (2024–2025) point to recurrent patterns: crowding at ration points, night‑time disputes around shared facilities, and delayed recognition of medical distress. Connectivity is often unreliable, power is scarce, and server‑based tools remain impractical. An on‑device estimator that works under these constraints is therefore not optional but necessary.

6‑C) Deployment & governance (practical plan).Pilot units:3–5 devices per camp sector (solar + local mesh).Operating model:protection officers validate alerts during routine patrols; weekly review calibrates thresholds.Data stewardship:a designated NGO focal point holds cryptographic keys; rotation and audit logs ensure continuity.Interoperability:CSV/JSON import‑export allows local teams to edit baselines and share lessons across sites without personal data.

7) Why this matters (key message).Without server‑scale AI, low‑power offline systems can still deliver the essential cycle ofdetect → alert → learn. Transparent and data‑minimal, it strengthens—rather than replaces—human judgment and aligns with GDPR, UNCRC, and CRPD. Costs are limited to solar + budget devices + local networking, allowing coverage of a camp for a few hundred to a few thousand dollars. By embedding human confirmation into the learning loop, the system avoids blind automation and becomes acollaborative toolthat grows more accurate with every check.

8) Collaboration request & evaluation.I would be honored to explore joint pilots with humanitarian teams and adapt this tool per your operational feedback. A live browser demo (≈48KB) and full offline code are available for field testing upon request. Suggested success metrics: median alert‑to‑response time; precision/recall by alert type; reduction in repeated high‑stress hotspots; and staff satisfaction with explainability.

9) Limitations & risk management.The estimator is not a replacement for professional judgment. It may produce false alarms when context changes abruptly; this is why human confirmation is integral. All configurations should be reviewed with protection, legal, and safeguarding leads before deployment. Where radio silence is mandated, the system runs strictly on‑device with logs exported only under authorization.

Summary:

The method proves that a fully explainable, ultra‑lightweight AI can run only in the browser. Swap country data for camp signals and connect alert → confirmation → learning, and the same engine becomes practical, field‑ready protection infrastructure for detecting violence, safeguarding vulnerable groups, and spotting medical emergencies early.Baseline data starts the process; real‑time feedback fine‑tunes it; the system evolves into a localized, adaptive safety detector.