

AI-Enabled LoRa Mesh Wearable for Personal Emergency Alerts Using Edge AI: A Review and Conceptual Framework

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Abstract- A personal alarm is useful only if it can send a message at the moment help is needed. A person who has fallen may be unable to reach a button, mobile coverage may be missing in remote or enclosed places, and a cloud service may be out of reach. Progress in embedded machine learning, inertial sensing and low-power long-range radio makes it realistic to build a wearable that screens body movement locally and relays a small alert through neighbouring radio nodes. This paper presents a focused narrative review of eight studies on LoRa mesh routing, wearable fall detection with edge inference, LoRaWAN-based wearable networks, radio localisation and multi-sensor emergency alerting. The studies are discussed under three themes: sensing and on-device classification, multi-hop alert transport, and system-level evaluation. Reported fall-detection accuracies of about 95.6–95.9% and an inference time below 37.84 ms show that local classification is feasible, yet these values come from individual datasets and prototypes and cannot be transferred to a different wearer, sensor or outdoor setting. None of the reviewed work evaluates the complete chain from body-worn motion sensing, through mesh relaying, to notification of a trusted contact. To address this gap, the paper outlines a conceptual seven-layer architecture that combines an IMU-based event score, a manual SOS path that bypasses classification, compact authenticated packets, duplicate-controlled relaying and explicit delivery-state reporting, together with evaluation metrics and a four-stage test plan. The main risks (false alarms, missed events, radio congestion, battery drain, location error, privacy loss and spoofed alerts) are examined. The proposed system is an assistive alert aid, not a guaranteed rescue service or a diagnostic device.

Keywords— Personal Safety, Wearable Sensors, Edge AI, LoRa Mesh, Fall Detection, Emergency Alert, Embedded Machine Learning

I. INTRODUCTION

People who work alone, travel through remote terrain or live independently can be hurt in a place where nobody is close enough to notice. Phone applications and wearable panic buttons already exist, yet most depend on one of two things: the wearer must be able to trigger the alarm, or a mobile or internet connection must be available. A device that recognises a risky movement pattern by itself and sends a short message over a low-power radio link would remove both dependencies, at least in part.

Three technologies make such a device plausible. LoRa offers long-range, energy-efficient links for small payloads [1]. Inertial sensors record body movement at low cost, and embedded machine

learning can classify short signal windows on a microcontroller or a nearby edge node [2]–[5]. LoRa, however, is a radio technique and not a mesh by itself: multi-hop forwarding, duplicate control and acknowledgement have to come from a routing layer, which is the subject of work on emergency messaging such as R-AODV [6]. In the same way, local inference removes the need for a cloud service during detection but cannot make sure that a radio message reaches anyone.

Existing studies treat these pieces separately. Fall-detection papers evaluate classifiers, routing papers evaluate message delivery, and survey and localisation papers discuss wearable networking and positioning [7]–[10]. Whether the pieces work together on a person in a real emergency has not been shown. This paper therefore (i) reviews the relevant literature, (ii) judges how far each reported

result can be relied upon, (iii) proposes a layered conceptual architecture with an explicit delivery-state model, and (iv) defines evaluation measures and a staged test plan. Results from the reviewed papers are reported as findings of those experiments and are never presented as predictions for the proposed design.

II. REVIEW METHODOLOGY

This is a focused narrative review. Eight primary studies were chosen because each addresses one component of the proposed system: LoRa mesh routing for emergency messages [6]; wearable fall detection with edge inference [2]–[4], [10]; LoRaWAN-based wearable networks [7]; radio localisation [8]; and multi-sensor emergency alerting [9]. They were published between 2022 and 2024. Three background sources on LoRa technology [1], the AODV protocol [11] and embedded inference runtimes [5] were added to fix terminology. Quantitative results are quoted as the original authors state them, and no figure from one study is combined with another to estimate how the proposed system would perform. Because no logged search of bibliographic databases was carried out, the review is narrative rather than systematic, and the number of screened records is not reported.

III. SENSING AND EDGE INTELLIGENCE FOR WEARABLE EVENT DETECTION

1. Motion Sensing and Manual Triggering

A three-axis accelerometer reports linear acceleration, and a gyroscope reports rotation rate. A fall-like event usually shows up as a sharp impact, a change in body orientation and a period of reduced movement afterwards, all of which can be read from short windows of IMU data. Signal quality depends on where the device is worn, how firmly the strap is fitted and how the sensor is oriented, so these conditions should be recorded and varied during testing.

A physical SOS control is a separate, deliberate input. An injured person should not have to wait for a classifier to decide, so the manual path should

bypass automatic scoring altogether. Other sensors need a clear justification. A pulse sensor is prone to motion noise and cannot diagnose a medical condition, and a voice-keyword detector raises consent and privacy concerns that call for on-device processing and a physical disable switch.

2. On-Device Fall-Detection Models

Paramasivam et al. combined several deep-learning architectures for wearable fall detection and compared inference on embedded computing platforms; their CNN–LSTM model with attention performed strongly under the study's own conditions [2]. A smart-home study built on accelerometer time series and an LSTM network reports 95.87% accuracy on its chosen dataset [3]. Salah et al. designed an accelerometer-based edge-AI detector and report 95.55% accuracy with an inference time below 37.84 ms [4], and a further IoT study describes real-time wearable fall detection connected to remote monitoring [10]. Quantised runtimes such as TensorFlow Lite Micro target this class of hardware [5].

Together, these works show that classification close to the sensor is practical. They do not reveal how often a genuine fall is missed or how often everyday movement raises a false alarm, because accuracy alone hides both. Sensitivity, specificity, precision, F1-score and per-wearer results are needed, and a model trained on one sensor, one group of volunteers or one indoor setting should not be assumed to carry over to another.

3. Location and Multi-Sensor Context

LoRaAid studies joint communication and localisation underground, where satellite positioning is often unavailable [8]. A catastrophe-alert system pairs LoRa environmental monitoring with an auxiliary vital-sign sensor [9]. Both show that one low-power network can carry several kinds of information, but neither shows that a single model can recognise falls, environmental hazards and medical events together; each event class needs its own definition, data and validation. Because location accuracy depends on the environment and the node layout, coordinates should be attached only when a valid estimate exists, labelled with their source and

age, and never described as something LoRa alone guarantees.

IV. LORA MESH COMMUNICATION AND ALERT DELIVERY

1. LoRa, LoRaWAN and Mesh Networking

LoRa trades data rate for range and energy economy, so it suits short messages rather than continuous streams [1]. A survey of LoRaWAN-integrated wearable networks covers activity recognition and remote monitoring and points out trade-offs in payload size, power, comfort, scalability and security [7]. LoRaWAN is normally organised as a star of end devices around gateways, so a multi-hop mesh needs either a separate routing layer or a different network design, and any evaluation should state which of the two is used.

2. Routing for Emergency Messages

AODV is a reactive protocol: a route is discovered only when needed, through route-request and route-reply messages, and broken links are reported with route-error messages [11]. R-AODV targets emergency messaging over a LoRa mesh and was examined with direct transmission, multi-hop forwarding and a failed neighbour of the gateway [6]. Its reported delays differ between the normal and failure cases, which shows that recovery time can matter as much as normal-path delay. Those values belong to that paper's topology and settings and should not be assumed for another network. For a personal alert, route discovery must be bounded in time and hops, every packet needs a unique identifier, and relays must not forward the same alert more than once.

3. Packet Design and Delivery States

An alert packet should be small and carry only what a responder needs: a device pseudonym, event type, event time, event identifier, a confidence band, battery level, hop count and, when valid, a location with a validity flag. Raw sensor streams should never be broadcast. Authentication, for example a message authentication code, makes it harder for a rogue transmitter to inject false distress calls. Each relay checks the event identifier and a hop or time-to-live limit before forwarding, drops duplicates and returns

an acknowledgement. Route choice can weigh link quality, remaining battery and recent failures.

If a route fails, the node may try another path or hold the alert for a limited time, but holding an alert is not delivering it. The interface should therefore separate four states: created, relayed, received by the gateway, and contact notified.

4. Gateway and Trusted-Contact Notification

The gateway checks the format and authenticity of each message and passes it to whatever backhaul exists, such as Wi-Fi, Ethernet or cellular service. It can sound a local alarm even when the internet is down. Notifying a remote contact depends on a working backhaul and a configured service, a dependency that should be explained to users during setup. A notification should state the event type, time, location status and how the contact can acknowledge or escalate.

V. EVALUATION PRACTICE AND METRICS

1. Classifier Validation

Windows cut from the same recording are strongly correlated, so a random split of windows between training and test sets can overstate accuracy. Splitting by participant or by session is the safer practice, and the split rule should be stated in the report. Test data should cover walking, sitting, lying, running, stumbling and carefully simulated falls under an approved protocol, with varied wearers, body sizes, clothing and device positions. Participants must never be asked to perform hazardous falls.

2. System-Level Metrics

Because an emergency device is judged by missed events and late alerts, model accuracy is not enough. Table I (given with the other tables after Section VI) lists the measures proposed for an integrated prototype. Network trials should vary hop count, node outages, obstructions and competing traffic.

Privacy, Security and Responsible Use Movement and location records can expose personal routines. Only necessary data should therefore be collected, raw signals processed

locally where practical, messages encrypted, devices authenticated and contact details protected, with a stated retention policy. A unique event identifier together with a message authentication code limits replay and spoofing, and firmware updates should be signed before release.

Frequent false alarms erode trust, while missed alerts create false reassurance. Users should be told what the system can detect and when it may fail. It must not claim to diagnose illness, confirm that a person is safe or guarantee rescue, and any use in workplaces, campuses or public places should respect the relevant consent, privacy and safety rules.

VI. COMPARATIVE ANALYSIS

Table II summarises the reviewed studies and Table III contrasts alternative alerting approaches. Reported values are not directly comparable because datasets, hardware, topologies and test conditions differ between studies.

Table 1: Proposed Evaluation Metrics

Metric	Meaning	Relevance
Sensitivity (recall)	True events detected ÷ all true events	Exposes missed events
Precision	Genuine alerts ÷ all alerts raised	Shows nuisance-alarm burden
F1-score	Harmonic mean of precision and recall	Balances the two measures
End-to-end latency	Time from trigger to gateway or contact receipt	How soon help is informed
Packet delivery ratio	Unique packets received ÷ packets sent	Network reliability
Route recovery time	Time to resume delivery after a failure	Resilience of the mesh
Energy per alert; battery life	Energy used per event and in normal use	Practical wearability
Location availability and error	Share of alerts with a valid fix, and its error	Prevents unsupported location claims

Table 2: Comparison of the Reviewed Studies

Study, year	Objective	Method / platform	Major reported finding	Limitation for this design
R-AODV, 2023 [6]	Emergency alerts over a LoRa mesh	AODV-based routing; direct, multi-hop and gateway-neighbour-failure cases	Delay differs between normal and failure scenarios	Topology- and test-specific; values not transferable
Paramasivam et al., 2024 [2]	Wearable fall detection and prevention	Deep-learning combinations incl. CNN–LSTM with attention; embedded platforms	Strong classification results in the study's setting	Dataset- and device-specific; small wearables have tighter memory and battery limits
Elderly fall prediction, 2023 [3]	Fall prediction for smart home-care	Accelerometer time series; LSTM	95.87% accuracy on the selected dataset	Laboratory activities may differ from real falls
Salah et al., 2022 [4]	Accelerometer-based fall detection	Edge-AI architecture	95.55% accuracy; inference time below 37.84 ms	Accuracy alone does not describe safety risk
LoRaWAN wearable survey, 2024 [7]	Wearable networks for activity recognition	Literature survey	Trade-offs in payload, energy, comfort, scalability and security	No prototype; LoRaWAN is not automatically a mesh

LoRaAid, 2024 [8]	Underground communication and localisation	LoRa-based joint system	Combines messaging and positioning for underground use	Accuracy depends on environment and node layout
Catastrophe alert, 2023 [9]	Risk mitigation with vital monitoring	LoRa environmental monitoring plus auxiliary vital-sign sensor	One LoRa network can carry alerts from different sensors	No evidence that one model handles all event types
Real-time wearable fall detection, 2022 [10]	Wearable detection linked to remote monitoring	IoT integration	Illustrates sensing, communication and monitoring working together	End-to-end delivery needs independent testing

Table 3: Alerting Approaches and Their Role in the Proposed Design

Approach	Strength	Limitation	Role in proposed design
Manual SOS only	Simple and under the wearer's control	Wearer may be unable to press it	Keep as an independent, top-priority trigger
Threshold-based motion rules	Cheap to compute and easy to explain	Can confuse daily actions with falls	Supporting evidence and fallback check
Edge ML classifier	Learns complex patterns without a cloud	Needs representative data and validation	Run locally on the wearable or edge node
Cellular / internet alert	Reaches remote contacts directly	Needs coverage and a working service	Gateway backhaul when available
Single LoRa link	Long range, low power, small messages	A blocked link isolates the device	Baseline for network comparison
LoRa mesh	Can route around a missing direct link	Adds delay, complexity and energy use	Multi-hop alert transport

The strongest design is not the one with the highest classifier score or the longest quoted radio range, but the one that keeps working when a component fails and that states its uncertainty plainly.

Edge inference lowers dependence on remote computing and a mesh adds alternative paths, yet neither replaces battery monitoring, radio planning, security and a dependable human response process.

VII. PROPOSED CONCEPTUAL ARCHITECTURE

1. Layered Design

Fig. 1 shows the proposed architecture, derived from the reviewed systems and kept modular so that each layer can be tested alone or replaced. The wearer carries a device containing an IMU, microcontroller,

LoRa radio, battery and SOS control (layers 1–2). Sensor data are cut into short overlapping windows, range-checked and filtered, then passed to a compact classifier and rule checks (layer 3). A decision stage combines the evidence, applies a persistence rule and may offer a brief cancel prompt (layer 4).

Surviving events become authenticated packets that travel through relay nodes (layer 5) to a gateway that notifies trusted contacts (layer 6).

Logs, staged tests and model updates after independent retesting form the review layer (layer 7). The manual SOS skips layers 3–4 and goes straight to packet creation.

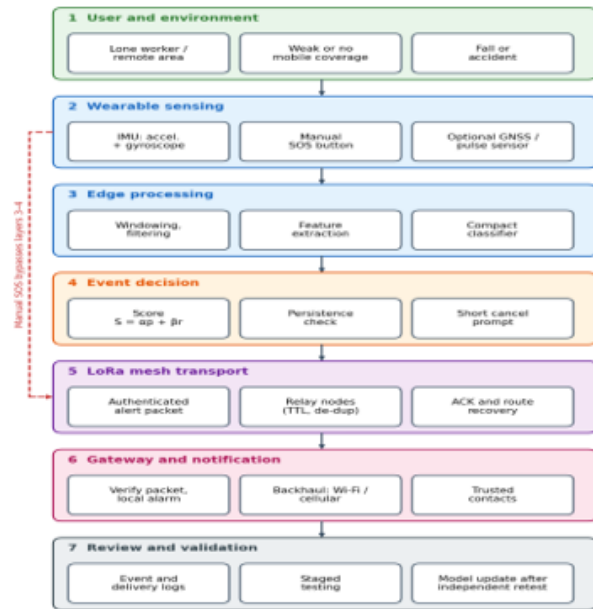


Fig. 1. Proposed conceptual architecture of the AI-enabled LoRa mesh personal-safety wearable (conceptual, not experimentally validated).

2. Event Scoring

Let p be the classifier's estimated probability that a window shows a target event, and r a score from supporting rules such as an impact peak followed by a lasting change in posture. An illustrative combined score is

$$S = \alpha p + \beta r, \quad \alpha + \beta = 1 \quad (1)$$

where α and β are tuned during validation. S is a design device and not a calibrated clinical probability. When S stays above a validated threshold for a set duration, the device prompts the wearer locally and prepares an alert.

3. Event Workflow

Fig. 2 traces one event from sampling to logging. The SOS check comes first so that a deliberate request is never delayed. Automatic events must pass the threshold-and-duration test and, where appropriate, a short cancel window, which reduces accidental alerts. The device then builds an authenticated packet and sends it; if no acknowledgement arrives it retries or tries another route and marks the alert as queued instead of delivered. Once the gateway

holds the packet it notifies the contacts and records the final state.

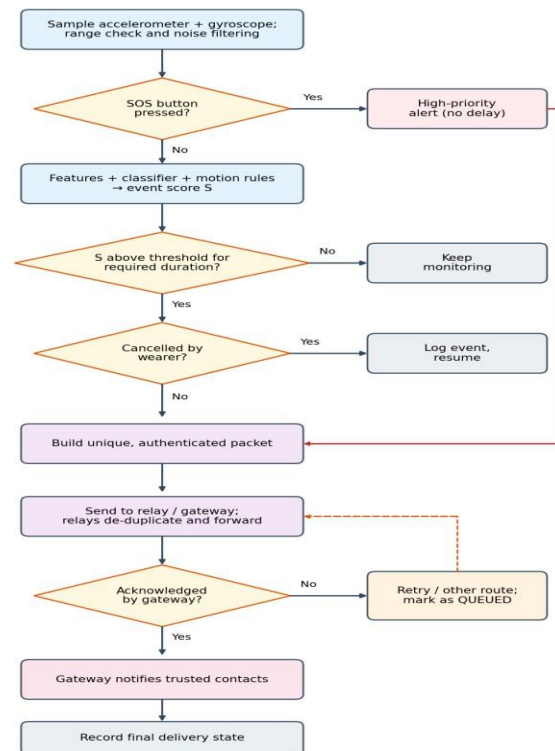


Fig. 2. Local event screening and alert delivery workflow.

4. Mesh Transport and Delivery States

Fig. 3 illustrates why a mesh helps: when the direct link between wearable and gateway is blocked, relays supply another path. Relays drop duplicates, decrease the hop limit and acknowledge each hop. The strip under the topology shows the four delivery states that the interface should expose to both the wearer and the contact.

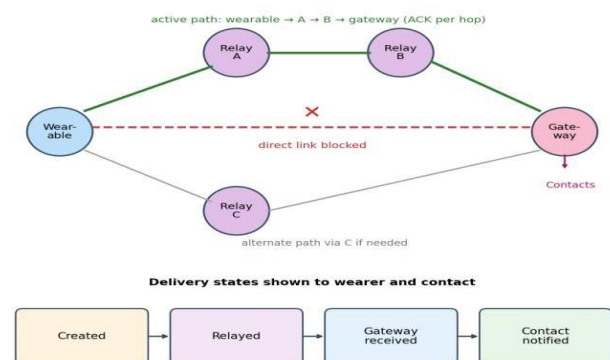


Fig. 3. Multi-hop alert delivery around a blocked direct link, with the four delivery states.

5. Staged Validation Plan

Fig. 4 outlines the plan. Stage 1 uses recorded or safely staged motion data to test preprocessing and model behaviour. Stage 2 tests the radio network on controlled layouts, measuring delivery, delay, duplicates, energy use and recovery at several distances and hop counts, with a relay switched off, a weak link, interference and a gateway outage. Stage 3 joins the two to confirm that a detected event produces the expected packet and that the gateway reports its true status. Stage 4, a limited supervised field trial, goes ahead only after risk review, informed consent and an agreed response procedure.

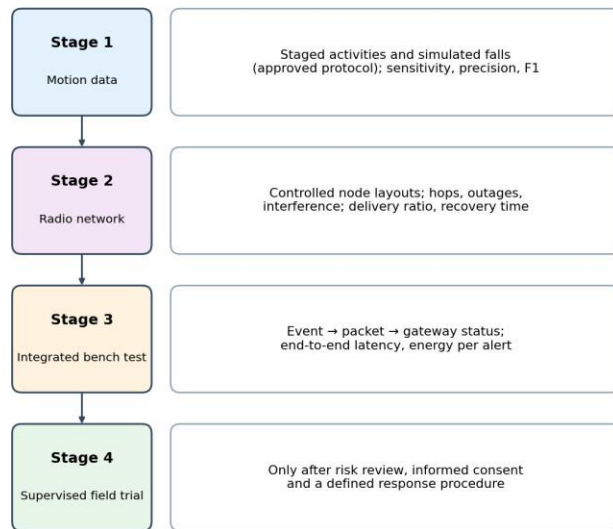


Fig. 4. Four-stage validation roadmap for the prototype.

A first prototype could pair an IMU with a low-power microcontroller (ESP32-class boards are convenient for early work), a LoRa transceiver and a rechargeable battery, running a quantised model under a TinyML runtime [5]. The radio layer should be built and tested separately from the model so that a fault can be traced to one or the other.

VIII. RESEARCH GAPS AND FUTURE DIRECTIONS

Gaps supported by the reviewed evidence. (i) No end-to-end evaluation: the reviewed papers cover individual parts using different devices and datasets,

and none follows an event from wearable motion to contact notification [2]–[4], [6]–[10].

(ii) Limited transfer of metrics: accuracy and latency figures come from particular datasets, hardware and topologies [2]–[4]. (iii) Event classes are studied separately: falls, environmental hazards and vital-sign monitoring are not shown to be handled by one model [9]. (iv) Location support depends on the environment and node arrangement [8]. (v) Missed-event rates and false alarms are not reported side by side.

Directions requiring investigation. Priorities include reproducible test protocols for the whole chain with diverse participants, reporting missed events next to false alarms; mesh trials under real obstruction that compare fixed routing, on-demand routing and limited store-and-forward under controlled failures; power-saving schemes assessed together with latency, since deep sleep may delay an alert; quantised models, consented personal calibration and sensor fusion; signed firmware updates and gateway redundancy; location treated as a separate subsystem that distinguishes a satellite fix, a network-based estimate and no location; and, before any safety-critical use, formal hazard analysis, independent assessment and a documented escalation process.

IX. CONCLUSION

The literature on edge fall detection and LoRa emergency messaging supports the feasibility of the individual blocks of a LoRa-mesh personal-safety wearable, but results from separate studies do not show that the integrated system will perform as well in practice. The proposed architecture keeps a manual SOS available, treats automatic detection as an estimate, uses compact authenticated packets and reports the true delivery state at every stage.

The next step is a carefully measured prototype rather than a claim of proven safety. Model tests should count missed events and false alarms, network tests should measure delivery and recovery under failure, and integrated tests should time the path from event to contact notification, with privacy,

battery life, location uncertainty and the human response designed in from the start. Until then, the system should be described as an assistive alert tool and not as a guaranteed rescue mechanism.

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