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EcoNav AI: An AI-Powered Disaster Assistance System with Offline Chatbot and Navigation

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Abstract : *Natural disasters frequently damage mobile towers and power supply, leaving affected people without internet access ex-actly when they need maps, first-aid instructions and a way to call for help. Most disaster-management applications depend on cloud services and centralized networks, so they fail under these conditions. This paper presents EcoNav AI, an offline-first mobile disaster assistance system that integrates (i) an on-device AI chat-bot for emergency and first-aid guidance, (ii) GPS-based navigation over pre-downloaded OpenStreetMap data, (iii) locally stored infor-mation on shelters, hospitals, food and water points, (iv) a one-tap SOS alert carrying the available GPS location, and (v) peer-to-peer messaging over Bluetooth Low Energy (BLE) and Wi-Fi Direct. All data are held in a local SQLite database so that core functions work without a network. We survey twenty recent studies on dis-aster communication, AI-based decision support and situational awareness, identify the lack of an integrated, resource-efficient offline platform, and propose a modular architecture together with Level 0 and Level 1 data-flow models, a local data schema and hardware/software requirements. This work reports the design stage (Phase I); implementation and field evaluation are planned as future work.*

Keywords: Disaster management, offline navigation, on-device language model, peer-to-peer communication, Bluetooth Low Energy, Wi-Fi Direct, OpenStreetMap, SOS alert.

I. INTRODUCTION

Floods, landslides, earthquakes and cyclones damage roads, power lines and telecommunication infrastructure at the same moment that people urgently need information. When mo-bile networks go down, online maps, emergency websites and cloud-hosted assistants become unreachable, rescue coordi-nation slows down, and affected individuals find it hard to identify safe locations, nearby hospitals or relief camps. In regions that are prone to monsoon floods and landslides, such as the state of Kerala, this loss of connectivity is a recurring risk rather than a rare event.

Research on technology for disaster management is broad. Existing work covers sensor-based early warning [1], AI-driven risk prediction and integrated management platforms [2, 3], and surveys of generative AI for damage assessment [4]. Another line of work restores communication through satel-lite links, UAV relays, mobile ad-hoc networks and mobile mesh networks [5–9]. Each of these addresses one part of the problem. Early-warning and prediction systems usually need a working network, communication systems rarely provide guidance or maps, and AI assistants are normally hosted in the cloud. A person standing in a flooded street without cover- age therefore has no single tool that can tell them what to do, where to go and how to reach someone.

Advances in lightweight, quantized language models, vector-map rendering and short-range wireless radios make it feasible to place these capabilities on an ordinary smart-phone. Satellite positioning does not require internet access, so GPS-based navigation can operate offline once map data have been downloaded in advance. Likewise, BLE and Wi-Fi Direct allow nearby phones to exchange data without any infrastructure.

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This paper proposes EcoNav AI, an offline-first mobile application that combines these capabilities into one system. Its principal contributions are:

- An integrated offline-first disaster assistance concept that brings together an on-device AI chatbot, GPS navigation on pre-downloaded OpenStreetMap data, local resource information, one-tap SOS and peer-to-peer communication in a single application.
- A literature survey of twenty recent studies, summarised in a comparison table and a capability matrix, which exposes the lack of an integrated offline platform.
- A modular system design comprising a layered architec-ture, a Level 0 and Level 1 data-flow model, a SQLite-based local data store, and hardware and software require-ments suited to mid-range smartphones.
- A plan for evaluating the system under simulated network outages, limited storage and low-battery conditions in the implementation phase.

The remainder of this paper is organised as follows. Section II reviews the literature, Section III presents the system design, and Section IV concludes and outlines future work.

II. LITERATURE SURVEY

We reviewed twenty recent studies and group them by the problem they address. Table I summarises their objectives, methods and limitations.

A. Early Warning, Prediction and Decision Support

Hema [1] proposed landslide monitoring and early warning with IoT sensors and an ESP32 microcontroller. The system gives real-time alerts but relies on internet or cloud connectiv-ity, has limited coverage, needs regular sensor maintenance and uses simple threshold alerts. Saleem et al. [2] combined machine learning and geospatial analysis to predict disaster risk and identify affected areas, but the approach needs suit-able datasets and computing power, which makes real-time use on low-powered phones difficult. Pandey et al. [3] proposed an intelligent disaster management system using real-time data, predictive AI, geolocation and resource management; it depends on continuous network access, and its models focus on earthquakes and floods. Raj et al. [4] surveyed AI and generative AI for damage assessment and response and noted that accuracy is not guaranteed, computing demands are high, and privacy, bias and misinformation concerns remain open.

B. Resilient and Peer-to-Peer Communication

Gupta et al. [5] designed a communication network that uses satellite links for disaster recovery, but the work is largely simulation-based and needs costly satellite hardware. Tran et al. [6] optimised UAV relay trajectories and resources to restore IoT communication, at the price of drones and spe-cialised infrastructure. Lien et al. [7] developed P2Pnet, a MANET-based emergency communication system that works without cellular towers; however, it concerns packet routing only and has no on-device AI, offline map navigation or one-tap SOS. Lenin et al. [8] presented a resilient communication and sensor-network framework with offline P2P links, which still faces scalability, energy-efficiency and real-world deploy-ment challenges. The same group [9] built an offline-first mobile mesh system for P2P messaging, which is limited to Android, short range and incomplete routing and security testing.

C. AI Assistants and Intelligent Navigation

Rajkumar et al. [10] built an offline chatbot that gives medi-cal guidance and hospital recommendations from pre-trained local data. Its knowledge is medical only, and it lacks offline routing, mesh messaging, SOS and shelter tracking. Shibu et al. [11] used Whisper, BERT with named-entity recogni-tion and Wav2Vec2 with Google Maps APIs to assist emer-gency call centres; the system targets call centres and de-pends on online map services. Zhou et al. [12] introduced AINav, an LLM-based skill tree with adaptive replanning for blocked paths, but its computational cost makes on-device ex-ecution difficult. Ibrahim et al. [13] inferred indoor topology from natural-language directions with LLMs on edge devices, limited to indoor environments and synthetic data. Nunez et al. [14] found that public trust strongly affects the adoption of AI disaster recommendations, and Lee et al. [15] outlined a responsible-AI roadmap for

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crisis management, which is a governance framework rather than a deployable system. These two studies motivate transparent, cautious presentation of AI guidance in EcoNav AI.

D. Situational Awareness, Victim Detection and Localization

Tejasvi et al. [16] used Android devices with sensors, thermal imaging and Wi-Fi to detect survivors; accuracy fell from 92% to 85% in low light and the work needs external hard-ware. Wiguna et al. [17] evaluated deep-learning models for building-damage mapping from satellite imagery, whose accu-

E. Research Gap

Table II contrasts three representative studies whose limita-tions are stated explicitly in the literature with the proposed system. Prior work either depends on connectivity or infras-tructure, covers one function (routing, medical advice or local-isation), or requires specialised hardware. No reviewed study provides on-device AI guidance, offline navigation, SOS and local resource information together with infrastructure-free messaging in one application. EcoNav AI is designed to fill this gap.

III. SYSTEM DESIGN

A. Design Goals

The design follows five goals derived from the gaps identified above. (1) Offline first: every core function must run from data stored on the phone, and the network is treated as an optional bonus. (2) Integration: guidance, navigation, resource lookup, SOS and messaging share one interface and one local database rather than being separate apps. (3) Resource efficiency: the application targets a mid-range smartphone with 4 GB of RAM, so models and map data must be quantized and region-limited. (4) Graceful degradation: if the language model cannot run or is not confident, the app falls back to static first-aid cards, and if no peer is in range, SOS alerts are queued locally. (5) Privacy: supported queries are processed on the device, which avoids sending personal information to a server.

B. System Architecture

Fig. 1 shows the layered architecture. The user interacts with the mobile application, which passes every action to an Ap-plication Controller. The controller dispatches requests to four functional modules: the AI, Navigation, Resource and Communication modules. A Storage Module provides a sin-gle data-access layer over the local SQLite database, so that modules do not manipulate files directly and all reads and writes are consistent. Results flow back through the controller to the user interface.

C. On-Device AI Assistance Module

The AI module answers emergency and first-aid questions with a lightweight quantized language model executed on the phone through ONNX Runtime Mobile or TensorFlow Lite. Candidate models are Qwen-1.5-0.5B and Phi-3-Mini [21]. Because a quantized Phi-3-Mini variant may be too large for a 4 GB device, the final choice will be made by measuring memory use and latency on target hardware, with the smaller model as the baseline.

To keep answers grounded in vetted content, the module fol-lows a retrieve-then-generate pattern over the first-aid knowl-edge base (D1), which holds curated first-aid and disaster-safety passages. For a query q, the module retrieves the k most relevant passages and conditions the model on them: racy varies by damage class and which needs suitable imagery. Halbgewachs et al. [18] used drone images, machine learning and 3D visualisation for flood situational awareness, but offer

$$r = \text{LLM } q, \text{Top-k}(q, D_1) , \quad (1)$$

no offline navigation or SOS. Chumyen [19] applied multi-agent coordination, computer vision and behaviour forecast-ing to water distribution, a narrow scope with a 5–10 minute prediction window. Ranjan et al. [20] proposed GeoSense, an offline localisation method based on device sensors and ambient Wi-Fi when GPS fails, which provides positioning only.where r is the displayed response. If retrieval returns no relevant passage or the model cannot be loaded, the module shows the matching static checklist from D1 instead of free-form text. Responses carry a short notice that they are general guidance and not a substitute for professional medical care. This cautious presentation reflects the trust and accountability concerns raised in [14, 15].

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Table I: Literature Survey Comparison

Ref.	Year	Objective	Methodology	Key Limitation
[1]	2025	Landslide monitoring and early warning	IoT sensors with ESP32, remote sensing	Needs internet/cloud; limited coverage; sensor upkeep; threshold alerts only
[2]	2025	Predict disaster risk and affected areas	AI/ML with geospatial analysis	Needs datasets and compute; hard on low-power phones
[3]	2025	Integrated disaster response and recovery	Real-time data, predictive AI, geolocation	Needs continuous network; AI limited to earthquakes and floods
[4]	2025	Review AI/GenAI for damage assessment	Survey of AI and generative AI	Accuracy not guaranteed; high data/compute; privacy and bias concerns
[5]	2025	Emergency communication when networks fail	Satellite-link network	Mostly simulation-based; costly satellite hardware
[6]	2022	Restore communication when ground networks fail	UAV relays with trajectory optimisation	Needs drones and special hardware; expensive
[7]	2024	Emergency communication when towers collapse	MANET-based P2P network	Packet routing only; no on-device AI, maps or SOS
[8]	2025	Communication when cellular networks collapse	Sensor network with offline P2P framework	Scalability, energy efficiency, real-world deployment
[9]	2026	Local messaging when the internet fails	Mobile mesh networking (P2P)	Android only; short range; routing and security testing pending
[10]	2024	Medical guidance and hospital recommendation	Offline chatbot on pre-trained local data	Medical only; no disaster features, routing or SOS
[11]	2025	Faster emergency call handling	Whisper, BERT+NER, Wav2Vec2, Google Maps APIs	Built for call centres; depends on map APIs
[12]	2025	Navigation when the path is blocked	LLM skill tree with adaptive replanning	High computational cost; poor real-world generalisation
[13]	2026	Indoor maps from natural-language directions	LLM-based topology inference	Indoor only; synthetic datasets
[14]	2026	Study public trust in AI disaster systems	Self-reported cross-sectional study	Only Peru and Chile; small, mostly male sample
[15]	2026	Ethical use of AI in crisis management	Responsible-AI governance roadmap	Mostly a framework, not a deployable system
[16]	2025	Survivor detection and location	Android with sensors, thermal imaging, Wi-Fi	Accuracy drops in low light (92% to 85%); external sensors
[17]	2024	Building-damage identification	Deep learning on satellite images	Accuracy varies by damage class; needs imagery
[18]	2023	Situational awareness for flood responders	Drone images, ML, 3D visualisation	Needs drone data; no offline navigation or SOS
[19]	2025	Fair water distribution in disaster relief	Multi-agent system, vision, behaviour forecasting	Water distribution only; 5–10 min prediction window
[20]	2025	Localisation when GPS fails	Symbolic regression on sensor and Wi-Fi signals	Positioning only; no complete emergency platform

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Table II: CAPABILITY COMPARISON WITH RELATED SYSTEMS

System	AI	Nav.	SOS	P2P	Res.
P2Pnet [7]	×	×	×	✓	×
Hospital chatbot [10]	✓a	×	×	×	×
GeoSense [20]	×	×	×	×	×
EcoNav AI (proposed)	✓	✓	✓	✓	✓

AI: on-device AI guidance; Nav.: offline map navigation; Res.: shelter/resource information. aMedical knowledge only. Entries for prior work follow the limitations stated in the respective papers.

D. Offline Navigation and Resource Identification

Before a disaster, the user downloads an OpenStreetMap (OSM) extract [22] for their region. Vector map tiles are rendered with the MapLibre mobile SDK, and the road net-work is stored locally so that routes can be computed on the device. The phone's GPS receiver provides the position with-out any internet link; the application only uses this position and the stored data to show the user's location and generate directions to a chosen destination.

The Resource module reads points of interest from the local database (D3). Hospitals, shelters, drinking-water points and assembly points are extracted from OSM tags during preparation of the offline package, and entries for relief camps, food distribution and similar facilities can be added or updated through peer exchange with relief-camp devices. The user can filter by type and sort by distance from the current position. In the current design, routing is based on the mapped road network; incorporating hazards and blocked roads is left for future work.

E. SOS Alert and Peer-to-Peer Communication

A single tap on the SOS button creates an alert packet

$$S = \langle id, t, \varphi, \lambda, a, c \rangle, \qquad (2)$$

where id is a device identifier, t the timestamp, (φ, λ) the latest GPS latitude and longitude, a the position accuracy, and c an optional emergency category. If no GPS fix is available, the last known position and its age are included. The packet is written to the alert and message log (D4) and then transmitted to nearby devices.

The communication module uses two short-range radios. BLE supports low-power discovery and small payloads such as SOS packets and acknowledgements, while Wi-Fi Direct supports higher-throughput exchanges such as longer mes-sages or resource updates between devices that support it. Rescue volunteers running the application receive the alert, display the sender's location and reply with a response or acknowledgement. Delivery is subject to device capabilities and radio range, and unacknowledged alerts remain queued in D4 and are retransmitted when a new peer is discovered. Multi-hop relaying is not part of the baseline design and is listed as future work.

F. Local Data Store

SQLite is chosen because it is serverless, embedded and widely supported on mobile platforms. Table III lists the planned tables, which correspond to the data stores in the data-flow diagrams.

G. Data-Flow Model

At Level 0 the system is a single process, EcoNav AI, that exchanges data with four external entities. The disaster vic-tim sends emergency queries, route requests, SOS requests

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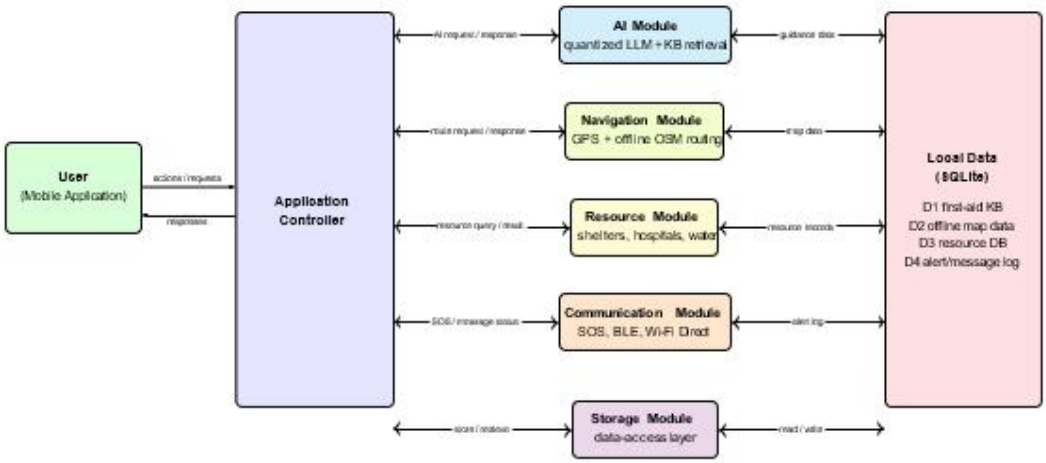


Fig. 1. Layered architecture of the proposed EcoNav AI system. All modules read from and write to a local SQLite database through the Storage Module; no component requires an internet connection.

Table III: PLANNED SQLITE DATA STORES

Store	Table	Contents
D1	first_aid_kb	First-aid and safety passages, topic tags, static checklists
D2	map_data	Region tiles, road-graph edges, point-of-interest index
D3	resources	Shelters, hospitals, food and water points, status, timestamp
D4	alerts, messages	SOS records, sent/received messages, acknowledgement state

Table IV
HARDWARE AND SOFTWARE REQUIREMENTS

Component	Specification / Purpose
Processor	Quad-core mobile SoC (e.g., Snapdragon 600)
Memory, storage	4 GB RAM; 2 GB for local model and maps
Radios	GPS, Bluetooth (BLE) and Wi-Fi (Wi-Fi Direct)
UI framework	Flutter or React Native (cross-platform app)
Inference engine	ONNX Runtime Mobile or TensorFlow Lite
Language model	Quantized LLM such as Qwen-1.5-0.5B or Phi-3-Mini
Maps	OpenStreetMap data; MapLibre mobile SDK
Local storage	SQLite
Platform	Android (primary) or other supported mobile OS

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and resource queries, and receives first-aid guidance, di-rections, SOS status and resource information. The GPS satellite supplies location coordinates. The relief camp ex-changes resource-status information, and the rescue volunteer exchanges SOS alerts, messages, responses and acknowledge-ments.

Level 1 (Fig. 2) decomposes the system into five processes: AI Chatbot (1.0), Offline Navigation (2.0), Resource Manage-ment (3.0), SOS Alert (4.0) and P2P Communication (5.0). The chatbot reads the first-aid knowledge base (D1). Navi-gation combines GPS coordinates with offline map data (D2) and shelter and hospital locations from the resource database (D3). Resource Management reads D3 and exchanges status updates with relief camps. The SOS process creates the alert record, stores it in the alert and message log (D4) and passes an SOS packet to the P2P process, which exchanges alerts, messages and acknowledgements with rescue volunteers over Wi-Fi Direct and BLE.

H. System Requirements

Table IV lists the requirements of the prototype. The hardware targets an ordinary mid-range Android smartphone. A cross-platform framework is proposed for the interface, although Wi-Fi Direct support differs between mobile platforms, so Android is the primary target.

I. Planned Evaluation

The implementation phase will evaluate the prototype with the following measurements: (i) response latency, peak memory and battery drain of the chatbot on target devices; (ii) correct-ness and safety of first-aid answers, reviewed against stan-dard first-aid references; (iii) route computation time and storage size of offline map packages for a district-level region;

(iv) BLE and Wi-Fi Direct range, SOS delivery success and delivery delay with several devices; and (v) behaviour under simulated network outage, limited storage and low-battery conditions. We have not yet carried out these experiments, and no performance claims are made in this paper.

IV. CONCLUSION AND FUTURE WORK

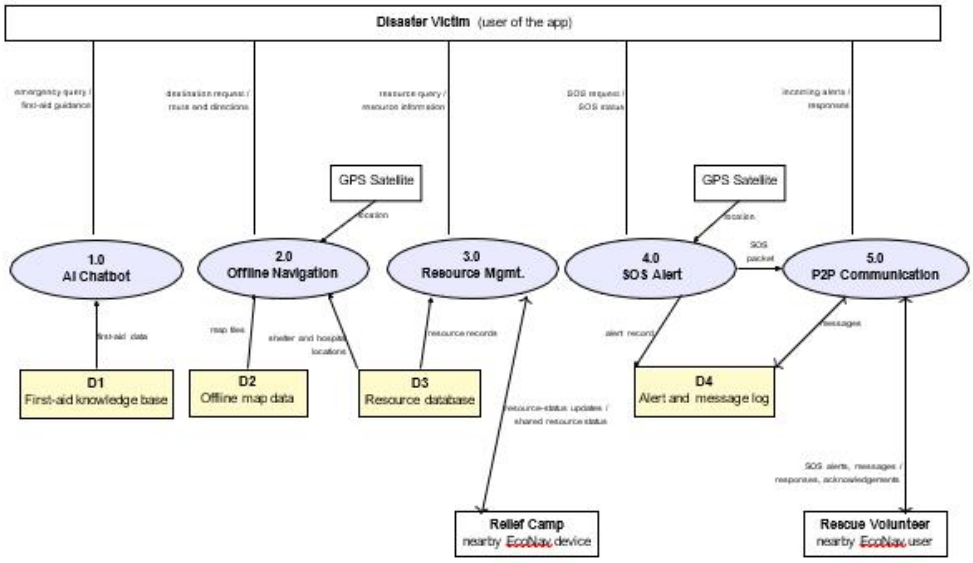


Fig. 2. Level 1 data-flow diagram of EcoNav AI showing the five main processes, four data stores and external entities.

successful implementation, accuracy of the stored data, device compatibility and the reliability of the offline functions, all of which remain to be verified in the next phase.

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This paper presented EcoNav AI, an offline-first disaster as-sistance system that integrates an on-device AI chatbot, GPS navigation on pre-downloaded OpenStreetMap data, locally stored resource information, one-tap SOS alerts and BLE/Wi-Fi Direct peer-to-peer communication. A survey of twenty recent studies showed that existing systems depend on con-nectivity or infrastructure, cover only one function, or need specialised hardware. In response, we proposed a modular architecture, a Level 0/Level 1 data-flow model, a SQLite data schema and a set of requirements suited to mid-range smartphones. The practical value of the system depends on

Future work includes the following directions.

- Implementation and testing: build the prototype and evalu-ate it under simulated outages, low battery, limited storage and different devices.
- Improved AI: optimise lightweight models for lower mem-ory and latency, and add multilingual (regional language) support.
- Hazard-aware navigation: incorporate mapped hazards, blocked roads and verified evacuation routes into the local map data, for example with an edge cost $w' = we (1 + \gamma he)$, where he is a hazard score.
- Extended P2P networking: investigate multi-hop mesh re-laying and cross-platform support to extend range beyond a single hop.
- Security and privacy: add authenticated, encrypted mes-saging and protection of location data.
- Resource coordination and IoT: synchronise shelter capac-ity, food, water and medical availability when channels exist, and explore sensor integration for early warning.
- Human activity estimation: explore the use of GPS, Blue-tooth, Wi-Fi signals and device sensors to estimate nearby human activity, subject to privacy constraints.

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