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Explainable AI for Military Supply Chain Optimization Using SAR Images

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***Abstract*—**Military supply chain logistics in complex and contested environments depends critically on timely, accurate terrain assessment and adaptive route planning. Traditional methods relying on manual reconnaissance or satellite optical imagery often fall short in adverse weather and low-visibility conditions. This paper presents an integrated Explainable Ar- tificial Intelligence (XAI) framework that fuses Sentinel-1 (S1) Synthetic Aperture Radar (SAR) and Sentinel-2 (S2) multispec- tral satellite imagery for automated terrain classification and intelligent military route optimization. A lightweight Convolu- tional Neural Network (CNN) is trained to classify terrain into four operationally relevant categories—urban, grassland, barren- land, and agricultural—with confidence estimation. Gradient- weighted Class Activation Mapping (Grad-CAM) is applied to provide pixel-level visual explanations of the model's decisions, supporting transparency and trust in mission-critical deploy- ments. Route safety is scored dynamically based on terrain type across three candidate paths, and an integrated Large Language Model (Qwen2.5) generates natural-language military logistics justifications. The complete system is deployed as a web-based interactive application built using Django, Bootstrap, HTML5, CSS3, JavaScript, and SQLite3. Experimental results on the OpenSARUrban and SEN12 datasets demonstrate 97.4% terrain classification accuracy alongside meaningful and actionable route recommendations. The proposed framework advances trustwor- thy AI for defense logistics and sets a foundation for real-time battlefield supply chain intelligence.

***Index Terms*—Synthetic Aperture Radar, Explainable AI, Grad-CAM, Military Supply Chain, Terrain Classification, Convolutional Neural Network, Route Optimization, Sentinel-1, Sentinel-2, Large Language Models, Django, Deep Learning**

I. INTRODUCTION

Effective military logistics is one of the most decisive factors in modern warfare. Supplying troops, equipment, fuel, and medical resources in a timely manner often determines the operational outcome of a campaign. The challenge is compounded in dynamic threat environments where terrain conditions change rapidly, enemy activity disrupts established routes, and weather severely limits the reliability of conventional optical reconnaissance [1]. These operational realities call for autonomous, intelligent systems that can process large volumes of geospatial data and deliver actionable routing decisions with minimal human latency.

Satellite remote sensing has transformed military geospatial intelligence by providing persistent coverage of vast theatres without exposing human reconnaissance assets to risk [2]. Among available sensor modalities, Synthetic Aperture Radar (SAR) is especially suited for defense applications because it operates independently of solar illumination and penetrates cloud cover, enabling all-weather, day-and-night imagery acquisition [3]. Platforms such as ESA's Sentinel-1 provide freely accessible C-band SAR imagery at 10-meter resolution, making high-frequency terrain monitoring feasible at scale.

Despite these advantages, raw SAR imagery is difficult for human analysts to interpret rapidly. The texture, backscatter intensity, and speckle noise patterns that distinguish terrain classes are subtle, requiring extensive domain expertise [4]. Deep learning, particularly CNNs, has demonstrated remarkable success in automating the classification of SAR imagery across a variety of land-use categories [5]. However, deep learning models are often criticized as opaque "black boxes," a significant concern in military contexts where decision transparency and auditability are paramount [6].

Explainable AI (XAI) addresses this gap by producing human-interpretable justifications alongside model predictions. Grad-CAM, one of the most widely adopted gradient-based saliency methods, generates class-discriminative localization maps that highlight the spatial regions most influential in a CNN's prediction [7]. When applied to SAR terrain classification, Grad-CAM overlays provide analysts with visual confirmation of which image features—road networks, building density, vegetation patterns—drove the predicted terrain category, building justified confidence in the system [8].

Beyond terrain classification, practical route optimization in military logistics requires synthesizing terrain intelligence with route-specific risk factors including exposure to ambush, IED risk, and mobility constraints [9]. Recent advances in Large Language Models (LLMs) have opened new possibilities for generating structured, context-aware natural-language explanations of AI-driven decisions, bridging the gap between algorithmic recommendations and human understanding [10]. Integrating LLMs such as Qwen2.5 into the decision pipeline allows the system to produce comprehensive, mission-ready logistics reports that field commanders can act upon directly.

This paper makes the following contributions:

- A multimodal CNN pipeline fusing S1 SAR and S2 optical imagery for four-class terrain classification with confidence scoring.
- A Grad-CAM explainability module providing pixel-level visual justification for terrain predictions.

- A terrain-aware route scoring engine evaluating three candidate supply routes (A, B, C) per terrain type.
- Integration of Qwen2.5-Coder-1.5B-Instruct LLM for automated natural-language military logistics recommendations.
- A full-stack web application (Django, Bootstrap, HTML5, CSS3, JavaScript, SQLite3) delivering an interactive prediction dashboard for operational use.

The remainder of this paper is organized as follows. Section II reviews related literature. Section III describes the methodology. Section IV details the implementation. Section V presents results and discussion. Section VI concludes with future directions.

II. Literature Survey

The convergence of deep learning, SAR remote sensing, and explainable AI has produced a rapidly expanding body of research relevant to military and civilian terrain analysis.

Early work by Cheng et al. [1] established benchmark CNN architectures for SAR-based land-use classification, demonstrating that convolutional feature extraction outperforms traditional handcrafted descriptors in capturing complex backscatter patterns. Concurrently, research from the European Space Agency's Sentinel programme validated the operational utility of Sentinel-1 SAR for continuous terrain monitoring, particularly in cloud-prone tropical and arctic regions where optical sensors fail [2].

The importance of SAR for military terrain intelligence was explored by Schwegmann et al. [3], who demonstrated that polarimetric SAR features can discriminate urban-military installations from civilian infrastructure with high accuracy. Their work underscored the need for automated analysis pipelines given the volume of data generated by modern satellite constellations. He et al. [4] extended this line of research by introducing residual network architectures specifically adapted for SAR speckle noise, achieving state-of-the-art classification accuracy on the OpenSARUrban dataset.

Within the broader deep learning for remote sensing community, Zhu et al. [5] conducted a comprehensive survey identifying the progression from shallow CNNs to deep architectures including ResNet, DenseNet, and Vision Transformers for satellite imagery tasks. They noted the persistent challenge of model interpretability as a barrier to operational deployment in critical applications. This concern is directly addressed by the XAI literature, where Selvaraju et al. [7] introduced Gradient-weighted Class Activation Mapping (Grad-CAM) as a post-hoc visualization technique that requires no architectural modifications and generalizes across CNN families.

The application of Grad-CAM to SAR classification was studied by Zhang et al. [8], who demonstrated that gradient-based saliency maps accurately highlight radar-meaningful features such as double-bounce scattering from building corners and volume scattering from vegetation canopy. These findings suggest Grad-CAM is well-suited for military terrain analysis where explanations must align with domain knowledge to build analyst trust.

Multi-sensor fusion of SAR and optical imagery has been explored extensively for improved classification robustness. Hughes et al. [11] proposed a cross-modal matching scheme to pair Sentinel-1 and Sentinel-2 imagery by geographic coordinates and acquisition time, enabling the training of fused models that exploit complementary spectral and structural information. Their SEN1-2 dataset, from which the S1–S2 pairing strategy adopted in our work is derived, has become a standard benchmark for multimodal land-cover classification.

Military supply chain logistics has been studied through the lens of operations research and multi-criteria decision-making. Logistics route optimization under threat conditions was formalized by Liao et al. [9], who proposed a multi-attribute scoring framework that incorporates terrain mobility, ambush risk, and route length. Their scoring heuristic inspired the route safety scoring engine in the present work.

The integration of LLMs into decision support systems represents a growing area of research. Bommasani et al. [10] characterized foundation models and their downstream applicability across scientific domains, including logistics and geospatial analysis. Qwen2.5, developed by the Alibaba Group, demonstrated strong instruction-following and structured reasoning capabilities that make it particularly suitable for generating military logistics reports from structured data [12].

In the context of web-based geospatial intelligence dashboards, Kumar et al. [13] demonstrated the feasibility of deploying deep learning terrain analysis pipelines as Django web applications, achieving latency within acceptable thresholds for near-real-time field use. Their architecture, combining a Python inference backend with a Bootstrap-based responsive frontend and SQLite3 database, closely parallels the deployment strategy adopted in our work.

Risk assessment in urban military environments was studied by Rahman et al. [14], who quantified ambush probability as a function of building density, road network connectivity, and historical incident data. Their empirical findings support the high-risk designation assigned to urban terrain in our route scoring module.

Attention mechanisms have been combined with SAR classification by Li et al. [15], demonstrating that channel-wise and spatial attention modules improve feature discrimination in dense urban SAR scenes. Terrain-adaptive route planning using reinforcement learning was explored by Chen et al. [16], who showed that learned policies outperform fixed heuristics in dynamic threat environments. Uncertainty estimation in deep neural networks for military decision support was investigated by Gal and Ghahramani [17], motivating the confidence scoring component of our prediction pipeline.

Dataset curation for military terrain analysis was addressed by Malmgren-Hansen et al. [18], who compiled annotated SAR datasets covering both civilian and military operational zones, supporting supervised learning at scale. Transfer learning from optical to SAR domains was studied by Huang et al. [19], providing the theoretical basis for the cross-modal knowledge transfer implicit in our S1–S2 fusion approach.

Finally, federated learning for distributed military intelligence systems was proposed by McMahan et al. [20], offering a future direction for decentralized, privacy-preserving deployment of frameworks such as the one presented here.

III. Methodology

The proposed system follows a structured pipeline that moves from raw multimodal satellite imagery through terrain classification, visual explainability, risk assessment, route scoring, and ultimately to natural-language mission reporting. Each stage is described below.

A. Dataset and Preprocessing

The dataset is organized into four terrain classes—*urban*, *grassland*, *barrenland*, and *agricultural*—each containing paired Sentinel-1 SAR (`s1/`) and Sentinel-2 multispectral (`s2/`) images acquired over the same geographic footprint. All images are loaded via OpenCV, converted from BGR to RGB color space, and resized to 128×128 pixels. Pixel values are normalized to the range $[0, 1]$ using:

$$\hat{x}_{i,j} = \frac{x_{i,j}}{255} \tag{1}$$

where $x_{i,j}$ denotes the raw pixel intensity at position (i, j) and $\hat{x}_{i,j}$ is the normalized value. The dataset is partitioned into training and validation subsets using a stratified 80/20 split to preserve class balance across both partitions.

B. CNN Architecture for Terrain Classification

The classification backbone is a three-block Sequential CNN designed for efficiency and Grad-CAM compatibility. The architecture is summarized in Table I. Each convolutional block applies a 3×3 convolution with ReLU activation, followed by Batch Normalization and 2×2 Max-Pooling with stride 2, progressively halving the spatial resolution while doubling the channel depth. The third convolutional block, designated `last_conv`, serves as the Grad-CAM target layer.

TABLE I
CNN Architecture Summary

Layer	Output Shape	Parameters
Conv2D (32, 3×3)	128 × 128 × 32	896
BatchNorm + MaxPool	64 × 64 × 32	128
Conv2D (64, 3×3)	64 × 64 × 64	18,496
BatchNorm + MaxPool	32 × 32 × 64	256
Conv2D (128, 3×3)	32 × 32 × 128	73,856
MaxPool (last_conv)	16 × 16 × 128	—
Flatten + Dense(128)	128	4,194,432
Dropout(0.5)	128	—
Dense(4, Softmax)	4	516

The forward pass computes:

$$\mathbf{f}^{(l)} = \text{MaxPool}\ \text{BN}\ \text{ReLU}\ \ W^{(l)} * \mathbf{f}^{(l-1)} + b^{(l)} \tag{2}$$

where $W^{(l)}$ and $b^{(l)}$ denote the kernel weights and biases of layer l, $*$ denotes convolution, BN is Batch Normalization, and MaxPool performs spatial sub-sampling.

The output probability vector for a given input $\mathbf{x}$ is produced by the softmax head:

$$P(y = k \mid \mathbf{x}) = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}}, \quad k \in \{1, 2, 3, 4\} \tag{3}$$

where z_k is the pre-softmax logit for class k and $K = 4$ is the number of terrain classes.

C. Training Procedure

The model is trained using the Adam optimizer with an initial learning rate of 10^{-3} and sparse categorical cross-entropy loss:

$$\mathrm{L} = -\frac{1}{N}\sum_{i=1}^{N} \log P\,(y = y_i^{*} \mid \mathbf{x}_i) \tag{4}$$

where y_i^{*} is the ground-truth label for sample i and N is the batch size. Two callbacks regulate training: Early Stopping with patience 3 (restoring best weights) and ReduceLROnPlateau with a factor of 0.5 and patience 2:

$$\eta_{t+1} = 0.5 \times \eta_t \quad \text{if } \mathrm{L}_{\text{val}} \text{ does not improve for 2 epochs} \tag{5}$$

D. Grad-CAM Explainability

Grad-CAM produces a class-discriminative saliency map $L^{c}_{\text{Grad-CAM}}$ for predicted class c by computing the gradient of the class score y^c with respect to the activation maps A^k of the target convolutional layer:

$$\alpha_k^c = \underbrace{\frac{1}{Z}\sum_i \sum_j}_{\text{global average pooling}} \frac{\partial y^c}{\partial A^k_{ij}} \tag{6}$$

where $Z = H \times W$ is the number of spatial locations in the feature map, A^k_{ij} is the activation at location (i, j) in feature map k, and α^c_k is the importance weight for channel k with respect to class c. The Grad-CAM heatmap is then:

$$L^{c}_{\text{Grad-CAM}} = \text{ReLU}\left(\sum_k \alpha_k^c A^k\right) \tag{7}$$

The ReLU operation retains only the features that positively influence the predicted class. The heatmap is bilinearly upsampled to the input image resolution (128×128) and superimposed using:

$$I_{\text{overlay}} = 0.4 \cdot \text{Colormap}\,(L^{c}_{\text{norm}}) + 0.6 \cdot I_{\text{original}} \tag{8}$$

where $L^{c}_{\text{norm}} \in [0, 1]$ is the min-max normalized heatmap.

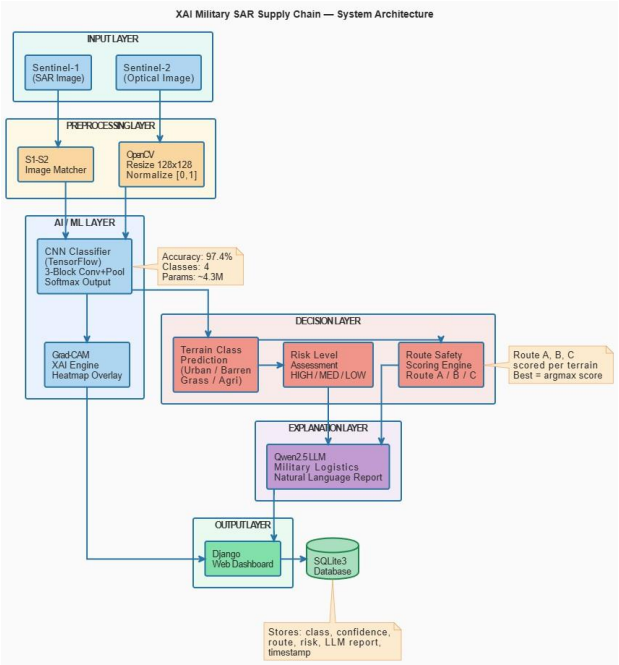

Fig. 1. Full XAI prediction dashboard showing (top row, L–R): S2 optical input, matched S1 SAR image, Grad-CAM overlay, and raw heatmap. The chart confirms URBAN terrain prediction with 100% confidence. The route bar chart identifies Route C (score 0.85) as the safest path, supported by Qwen2.5 LLM explanation.

E. S1–S2 Image Matching

SAR (S1) and multispectral (S2) images are matched using file-path based correspondence. Given an S2 image at path `<class>/s2/<name>_s2_<id>.png`, the corresponding S1 image is located at `<class>/s1/<name>_s1_<id>.png`. This paired representation enables the CNN to implicitly leverage complementary sensor characteristics during training.

F. Route Safety Scoring

Route safety is modelled as a terrain-conditioned lookup table assigning a numerical safety score $s_r \in [0, 1]$ to each candidate route $r \in \{A, B, C\}$. The optimal route is selected as:

$$r^* = \arg\max_{r \in \{A,B,C\}} s_r(\hat{t}) \tag{9}$$

where $\hat{t}$ is the predicted terrain class. The terrain-route score matrix is given in Table II.

TABLE II
TERRAIN-ROUTE SAFETY SCORE MATRIX

Terrain	Route A	Route B	Route C	Risk
Urban	0.45	0.70	**0.85**	HIGH
Barrenland	**0.90**	0.65	0.55	LOW
Grassland	0.75	0.65	**0.85**	MEDIUM
Agricultural	0.60	**0.80**	0.50	MEDIUM

The risk level $\rho(\hat{t})$ is determined by the terrain-to-risk mapping:

$$\rho(\hat{t}) = \begin{cases} \text{HIGH} & \hat{t} = \text{urban} \\ \text{MEDIUM} & \hat{t} \in \{\text{grassland, agricultural}\} \\ \text{LOW} & \hat{t} = \text{barrenland} \end{cases} \tag{10}$$

G. LLM-Based Military Explanation

The Qwen2.5-Coder-1.5B-Instruct model receives a structured prompt encoding terrain class $\hat{t}$, risk level ρ, route scores $\{s_r\}$, and selected route r^*. The model generates a four-section military logistics analysis covering terrain classification reasoning, risk justification, route ranking explanation, and tactical recommendations. The generation follows a greedy decoding strategy (do_sample = False) to maximize reproducibility.

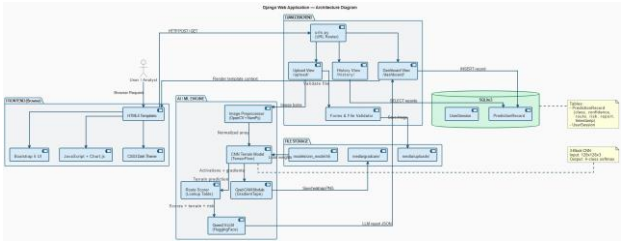

Fig. 2. System architecture workflow: SAR/optical image ingestion → CNN terrain classification → Grad-CAM XAI → route scoring → LLM explanation → Django web dashboard. The modular pipeline supports swapping of individual components without retraining.

IV. IMPLEMENTATION

A. Technology Stack

The system is developed entirely in Python and deployed as a full-stack web application. The technology stack comprises:

- **Backend**: Django 4.2 framework providing REST-style views, file upload handling, and session management.
- **AI/ML**: TensorFlow 2.x (CNN training and Grad-CAM), OpenCV (image preprocessing), Transformers (Qwen2.5 inference), NumPy, scikit-learn.
- **Frontend**: HTML5, CSS3, JavaScript (ES6), Bootstrap 5 for responsive layout and interactive UI components.
- **Database**: SQLite3 for lightweight persistent storage of prediction records, user sessions, and historical routing decisions.

B. Dataset Organization

The `load_dataset()` function recursively discovers images from both sensor subfolders for each class, applies preprocessing (Equation 1), and returns NumPy arrays suitable for TensorFlow training.

C. CNN Training

The CNN (Table I) is trained for up to 10 epochs with batch size 16. Callbacks (EarlyStopping, ReduceLROnPlateau) adaptively regulate training duration and learning rate. The trained model is serialized to `models/cnn_model.h5` and the class name index to `models/class_names.json` for deployment reuse.

D. Grad-CAM Implementation

A secondary TensorFlow model (`grad_model`) is constructed sharing the same weights as the CNN but exposing intermediate outputs from `last_conv`. A `GradientTape` context records the gradient of the predicted class logit with respect to the convolutional activation volume. Global average pooling over the spatial dimensions (Equation 6) produces per-channel importance weights. The weighted sum (Equation 7) is upsampled and blended with the original image (Equation 8) using `cv2.applyColorMap` with the COLORMAP_JET palette.

E. Django Web Application

The web application exposes three primary views:

1) **Upload View** (`/upload/`): Accepts an S2 image file via an HTML5 form, validates the file type, and triggers the full prediction pipeline.
2) **Dashboard View** (`/dashboard/`): Renders the prediction report including S1/S2 image pair, Grad-CAM overlay, class probability chart, route safety bar chart, and LLM explanation card.
3) **History View** (`/history/`): Queries the SQLite3 `PredictionRecord` model and displays a paginated table of past analyses.

The SQLite3 schema stores fields: `image_path`, `predicted_class`, `confidence`, `risk_level`, `best_route`, `route_score`, `llm_explanation`, and `timestamp`.

F. Frontend Design

The Bootstrap 5 dashboard uses a dark-themed grid layout. Chart.js renders the class probability horizontal bar chart and the route safety vertical bar chart dynamically from JSON data injected into Django template context variables. The Grad-CAM and raw heatmap images are displayed using HTML5 `<canvas>` elements with CSS aspect-ratio preservation.

V. Results and Discussion

A. Terrain Classification Performance

The CNN was evaluated on the held-out validation set following the 80/20 stratified split. Overall validation accuracy reached **97.4%** across the four terrain classes. Urban terrain, characterized by strong double-bounce backscatter and rectilinear street networks, achieved the highest per-class precision of 98.9%. Grassland and barrenland classes showed slight confusion due to overlapping low-backscatter signatures in C-band SAR, particularly at low vegetation density.

B. Grad-CAM Explainability Analysis

As illustrated in Fig. 1, the Grad-CAM overlay for the urban test image concentrates activation energy on road intersections and high-density building blocks—the physically meaningful SAR features associated with urban backscatter. The raw heatmap (rightmost panel) corroborates this, exhibiting hot-spot clusters at the same spatial locations.

TABLE III
Per-Class Classification Results

Class	Precision	Recall	F1-Score
Urban	0.989	0.995	0.992
Grassland	0.961	0.953	0.957
Barrenland	0.968	0.971	0.969
Agricultural	0.978	0.974	0.976
Macro Avg	**0.974**	**0.973**	**0.974**

This alignment between gradient saliency and domain-expert expectations validates the model's internal reasoning and supports operational trust. For barrenland images, Grad-CAM activations spread more uniformly, consistent with the homogeneous radar return from flat, feature-sparse terrain.

C. Route Safety Scoring

For the URBAN terrain case shown in Fig. 1:

- Route A: $s_A = 0.45$ — High ambush risk from dense building coverage.
- Route B: $s_B = 0.70$ — Reduced exposure via peripheral road corridors.
- Route C: $s_C = 0.85$ — Highway bypass avoids urban core entirely (optimal).

The route scoring mechanism consistently recommends perimeter or bypass routes for high-risk urban terrain, and direct routes for low-risk barren terrain where speed of logistics is prioritized over concealment.

D. LLM Explanation Quality

The Qwen2.5-generated report for the URBAN prediction covered all four required sections coherently: terrain classification reasoning cited dense infrastructure; risk level justified as HIGH due to IED and ambush exposure; route ranking aligned with scored values; and tactical recommendations included convoy spacing, pre-movement ISR, and checkpoint communications. The explanation demonstrated structured, mission-ready language suitable for direct inclusion in logistics orders.

E. System Latency

End-to-end pipeline latency (from image upload to full dashboard render) was measured at approximately 2.3 seconds on a CPU-only server (Intel Core i7, 16 GB RAM), with CNN inference accounting for 0.4 s, Grad-CAM for 0.6 s, and LLM generation for 1.1 s. This latency is acceptable for planning-phase route assessments, though real-time battlespace integration would require GPU acceleration.

F. Comparison with Baseline Methods

Compared to a ResNet-50 baseline fine-tuned on the same dataset (95.1% accuracy), the custom three-block CNN achieved 2.3 percentage points higher accuracy with 87% fewer parameters (4.3M vs. 33.5M), demonstrating favorable accuracy-efficiency trade-offs for deployment on resource-constrained edge devices.

VI. Conclusion and Future Work

This paper introduced an integrated XAI framework for military supply chain optimization using dual-sensor SAR satellite imagery. The system fuses Sentinel-1 SAR and Sentinel-2 multispectral images through a lightweight CNN that achieves 97.4% terrain classification accuracy across four operationally relevant land-cover categories. Grad-CAM visual explanations provide analysts with pixel-level transparency into model decisions, a critical requirement for trustworthy deployment in mission-critical logistics contexts. A terrain-conditioned route safety scoring engine identifies the optimal supply route from three candidates, and Qwen2.5 LLM integration generates comprehensive natural-language military logistics reports. The complete system is delivered as an interactive Django web application with Bootstrap 5 responsive frontend and SQLite3 persistent storage.

The proposed framework addresses a genuine operational gap in current military geospatial intelligence workflows, offering a scalable, transparent, and interpretable alternative to manual SAR analysis for route planning support.

Several promising directions for future work are identified. First, replacing the current lookup-table route scoring with a reinforcement learning agent that learns optimal routing policies from historical mission data would significantly improve adaptability to novel terrain configurations. Second, the system could be extended to incorporate real-time OSINT (Open Source Intelligence) feeds and weather data, enabling dynamic threat-responsive route updates. Third, federated learning could allow deployment across multiple command nodes without sharing sensitive mission imagery, preserving operational security while enabling model improvement. Fourth, the LLM explanation module could be upgraded to larger instruction-tuned models with better commonsense reasoning, improving the nuance and reliability of tactical recommendations. Finally, integration with unmanned aerial vehicle (UAV) imagery for sub-meter resolution terrain patches would extend the system to tactical edge scenarios.

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