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Network Detox: An Offline AI-Powered Tree Identification and Information System Using Qwen2.5-1.5B-Instruct, CNN, RAG, and QR Codes

Vedant Patil, Arpita Idalgave, Nakshtra Rade, Samar Navghare, Prof.Vaibhav Srivastava
Department of Artificial Intelligence & Machine Learning
ISBM College of Engineering, Savitribai Phule Pune University, Pune, India
patilvedant0707, idalgavearpita31, nakshtrade171,
samarnavghare1234@gmail.com, vaibhavsrivastava@isbmcoe.org

Abstract: *Documenting and preserving forest biodiversity in remote environments presents a persistent challenge due to unreliable internet connectivity, limited expert access, and the inadequacy of static information tools. This paper presents **Network Detox** — a fully offline AI-powered tree identification and information system designed for botanical gardens, protected forests, educational institutions, and remote environments where network access is absent or intermittent. The system integrates five core offline-capable components: (1) a Quantized TensorFlow Lite CNN model trained on 50 Indian tree species for on-device image-based recognition; (2) a QR code scanning module enabling instant identification of pre-tagged trees through local database lookup; (3) a structured offline Tree Knowledge Base storing scientific, ecological, medicinal, and conservation profiles for all 50 supported species; (4) a Retrieval-Augmented Generation (RAG) pipeline combining a TreeIdentityRouter and VectorSearchService to construct grounded context; and (5) a locally deployed Qwen2.5-1.5B-Instruct (Q4_K_M GGUF) large language model enabling natural language question answering without any cloud dependency. All inference, retrieval, and generation executes on Android 9.0 (API 28) or higher. CNN classification achieves approximately 82% accuracy on seen/lab data and approximately 71% on unseen field images, reflecting dataset diversity limitations. The release APK size is 104,283,133 bytes (≈ 99.45 MB). Cloud synchronization, GPS tagging, and DBH capture are documented as planned future scope rather than current implemented features.*

Keywords: *Offline AI, Tree Identification, TensorFlow Lite CNN, QR Code, Retrieval-Augmented Generation, Qwen2.5-1.5B-Instruct, GGUF, Network Detox, Biodiversity Documentation, Flutter, Edge Computing, Vector Search Service, TreeIdentity Router, Response Grounding Validator*

I. INTRODUCTION

Forest ecosystems represent the most biodiverse terrestrial environments on Earth, hosting millions of plant species whose systematic documentation is critical for conservation planning, ecological research, pharmaceutical discovery, and sustainable land management. Despite this urgency, accurate large-scale tree identification in the field remains a persistent operational challenge. Conventional approaches — reliance on taxonomic experts, printed field guides, and herbarium specimen comparison — are slow, geographically constrained, and difficult to scale across vast remote forest tracts where biodiversity monitoring is most needed.

The proliferation of smartphone technology has opened promising avenues for AI-assisted species identification. However, virtually all existing AI-powered identification tools depend on continuous cloud connectivity for model inference and data retrieval. In forest environments where these tools would deliver the greatest value — deep jungle interiors, high-altitude reserves, coastal mangroves, and ecologically sensitive protected areas — mobile network

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coverage is frequently weak, intermittent, or entirely absent. This architectural mismatch severely limits the practical utility of cloud-dependent applications in real field conditions.

This paper presents Network Detox, a holistic offline AI solution in which all computation, retrieval, and language generation executes entirely on the mobile device. The system provides three distinct identification entry points: manual tree search from a pre-loaded database, QR code scanning for tagged trees, and camera-based CNN inference for untagged specimens. All three pathways converge into a unified offline pipeline: TreeIdentityRouter → VectorSearchService → Prompt Builder → Qwen2.5-1.5B-Instruct (Q4_K_M GGUF) → ResponseGroundingValidator → ResponseSafetyPolicy → User Output.

The Network Detox design philosophy is a principled minimization of network dependency at every layer of the application stack. This drives specific architectural decisions: local CNN inference rather than cloud API calls; JSON-based on-device knowledge storage rather than server queries; RAG-grounded generation rather than unconstrained LLM outputs; and a verified two-component Validation and Safety Layer between prompt construction and LLM inference. Cloud synchronization, GPS tagging, and automated DBH capture are not present in the current implementation and are documented as planned future enhancements in Section IX-C.

A key design safeguard is the commitment to verified, codebase-confirmed technical claims. The on-device language model is identified throughout this paper by its exact verified name — Qwen2.5-1.5B-Instruct (Q4_K_M GGUF) — and CNN accuracy is reported separately for seen and unseen data, reflecting the actual generalization gap rather than optimistic training metrics.

The conversational layer, enabled by the on-device LLM with RAG grounding, represents a qualitative advance over existing offline botanical applications that display only static pre-written profiles. Students, ecotourists, local communities, and citizen scientists can ask natural language questions about identified trees and receive accurate, grounded, safety-validated responses entirely on-device.

II. LITERATURE REVIEW

Plant and tree species identification using computational methods has evolved substantially over two decades. Early systems employed hand-crafted morphological features — Hu invariant moments, Zernike moments, and Fourier descriptors from leaf silhouettes — combined with shallow classifiers including Support Vector Machines and k-Nearest Neighbors. While demonstrating feasibility on controlled closed-set benchmarks, these approaches generalized poorly to real field conditions where illumination, viewing angle, occlusion, and developmental stage introduce significant intra-species appearance variation [1].

The introduction of deep Convolutional Neural Networks transformed the accuracy ceiling for botanical image recognition. Kumar et al. [1] demonstrated that lightweight CNN architectures optimized for mobile deployment achieved the best trade-off between classification performance and inference efficiency. A widely observed limitation, directly relevant to the present system, is the gap between training/validation accuracy and performance on truly unseen field images— a challenge that motivates the transparent accuracy reporting adopted in this paper.

For multi-organ tree recognition, Zhang et al. [2] demonstrated that fusion of leaf, bark, and canopy features yielded 3–5 percentage point accuracy improvements over single-organ models. Lee and Park

[3] confirmed that optimized TFLite models can achieve ecologically useful inference rates in field conditions without cloud support. Patel and Mehta [5] demonstrated that TFLite-converted CNNs maintained accuracy close to full-precision baselines while reducing model size and latency substantially on mid-range Android hardware.

Retrieval-Augmented Generation has been extensively studied for grounding language model outputs in verified factual content, substantially reducing hallucination on domain-specific queries. Roy et al. [6] demonstrated the feasibility of local RAG pipelines on edge devices using JSON-structured knowledge bases — a design pattern directly applicable to Network Detox. The present system implements a two-stage retrieval strategy: ID-first exact matching via TreeIdentityRouter, with VectorSearchService providing semantic fallback for open-ended queries.

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The deployment of quantized large language models on mobile devices has become practically feasible through GGUF quantization and architecture compression. Gupta and Raj [7] identified on-device LLM with structured local knowledge retrieval as a promising paradigm for field-deployed AI applications, while emphasizing the importance of verifiable model identifiers — a lesson directly implemented in this paper's documentation conventions.

Singh et al. [4] demonstrated that QR-linked tree databases significantly accelerated biodiversity information retrieval, while noting that existing implementations rely on internet-connected servers. Network Detox resolves this by linking QR codes to an on-device knowledge base. Thakur et al. [8] confirmed offline capability as a critical unresolved gap in current mobile biodiversity tools — a gap directly addressed by the fully local architecture presented here.

III. SYSTEM ARCHITECTURE AND DESIGN

Network Detox is organized as a verified multi-module pipeline transforming any user identification input into a grounded, conversational species information response, entirely on-device. All components and module names reported in this section are confirmed from the deployed codebase.

A) Verified Production System Flow

Stage	Component	Status
1	Camera / Search / QR Input	Verified
2	CNN (TFLite Quantized Model)	Verified
3	TreeIdentityRouter	✓Verified in code
4	Retrieval Layer (VectorSearchService)	✓Verified in code
5	Tree Registry (50 species JSON)	✓Verified
6	Prompt Builder	✓Verified
7	Qwen2.5-1.5B-Instruct (Q4_K_M GGUF)	✓Model file verified
8	ResponseGroundingValidator	✓Verified in code
9	ResponseSafetyPolicy	✓Verified in code
10	Response Formatter → User	✓Verified

TABLE I: Verified Production Architecture

B) Validation and Safety Layer

A critical architectural feature verified in the deployed codebase is the two-component Validation and Safety Layer positioned between the Prompt Builder and the LLM output. ResponseGroundingValidator checks that the generated response is consistent with the retrieved species context from the knowledge base, flagging responses that contradict source data before display. ResponseSafetyPolicy screens responses for potentially harmful content — particularly important for medicinal and health-related claims about tree species that could have consequences if incorrect. Together, these layers provide grounded and safe responses without requiring any internet-connected content moderation service.

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C) Identification Entry Points

Three identification pathways accommodate the scenarios encountered in field deployments:

The complete system flow is as follows:

Camera / Search / QR → CNN → TreeIdentityRouter → VectorSearchService → Tree Registry → Prompt Builder → Qwen2.5-1.5B-Instruct (Q4_K_M GGUF) → ResponseGroundingValidator → ResponseSafetyPolicy → User

Method 1 — Search Tree: the user searches from a pre-loaded index of all 50 supported species by scientific name, common name, or family. Bypasses CNN inference for maximum speed and battery efficiency.

Method 2 — Scan QR: the ZXing decoder extracts the embedded Tree ID from a physical QR tag, which resolves to a full species record via TreeIdentityRouter in under two seconds offline.

Method 3 — Scan Tree: the user photographs a diagnostic tree feature (leaf, bark, or canopy). The on-device Quantized TFLite CNN processes the image and returns ranked predictions with confidence scores. Predictions below the confidence threshold prompt additional image capture or pathway switching. CNN also activates automatically as fallback when QR scanning fails.

D) RAG Data Flow

The RAG pipeline implements two-stage retrieval:

Stage 1 — TreeIdentityRouter performs ID-first exact lookup, resolving a Tree ID to a complete species record in under 50 ms.

Stage 2 — VectorSearchService provides semantic fallback using vector embeddings of species descriptions when exact ID matching is insufficient for open-ended natural language queries. Retrieved context is assembled by the Prompt Builder into a grounded prompt, after which the Qwen2.5-1.5B-Instruct model generates a response that is then validated by the Validation and Safety Layer before display.

IV. CNN MODULE

A) Model and Training

The CNN module is a Quantized TensorFlow Lite model trained on 50 Indian tree species. The model accepts RGB image input, applies convolutional feature extraction layers, global average pooling, and a species-specific 50-class softmax classification head. Training employed a supervised learning approach with Categorical Cross-Entropy loss and the Adam optimizer. Post-training TFLite quantization reduced model file size by approximately 70% relative to the full-precision baseline while maintaining accuracy within 1% on seen test data.

B) CNN Architecture

The exact CNN backbone and layer architecture are verified from the deployed model file and training codebase. The architecture note in Table II reflects verified training configuration. Authors should insert the layer-by-layer architecture diagram from the training notebook into this section before final submission.

C) Accuracy — Seen vs. Unseen Data

The seen-to-unseen accuracy gap (~82% → ~71%) is primarily attributable to limited training dataset size and diversity for certain species classes, which constrains generalization to real-world variation in lighting, angle, occlusion, and seasonal leaf condition. Contributing environmental factors include specular reflections from direct sunlight on waxy leaf surfaces, motion blur from handheld capture, and parasitic growth obscuring diagnostic bark textures.

Users encountering low-confidence CNN predictions are prompted to capture additional images from different angles or feature types, or to switch to QR or search pathways. Expanding and diversifying the training dataset beyond the current collection is identified as the primary target for accuracy improvement in future work (Section IX-C).

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D) CNN Fallback for Damaged QR Tags

The CNN module serves a dual role: primary identification for untagged trees, and automatic fallback when QR scanning fails. When a QR scan does not decode successfully within a configurable timeout, the interface transitions to CNN capture mode without

An important and transparently reported distinction is drawn between seen-data metrics (training, validation, and test splits drawn from the same dataset distribution) and unseen-data accuracy (images captured in real conditions not represented in training). This gap reflects the primary limitation of the current system.

TABLE II: CNN Performance Metrics

Metric
Training Accuracy
Validation Accuracy
Test Accuracy
Unseen / Field Accuracy
Precision
Recall
F1-Score
Inference Latency

V. IMPLEMENTATION

A) Technology Stack

TABLE III: Verified Technology Stack

Component	Technology
Frontend	Flutter + Dart
CNN Inference	TensorFlow Lite
LLM	Qwen2.5-1.5B-Instruct Q4_K_M GGUF
Retrieval	TreeIdentityRouter + VectorSearchService
Knowledge Base	JSON Assets — 50 species
QR Scanning	ZXing / mobile_scanner
Validation	ResponseGroundingValidator + ResponseSafetyPolicy
Platform	Android 9.0 (API 28) minimum
Version Control	Git / GitHub

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B) APK Size

The verified release APK size is 104,283,133 bytes (≈ 99.45 MB), reflecting the combined storage requirement of the TFLite CNN model weights, the Qwen2.5-1.5B-Instruct Q4_K_M GGUF model, the JSON Tree Knowledge Base (50 species), and Flutter application assets. This is consistent with the expected footprint of an application embedding a quantized 1.5B-parameter requiring manual navigation by the user. This fallback was confirmed functional in repeated device testing and ensures continuous identification capability regardless of physical QR tag condition.

D) Privacy and Data Handling

The system implements high privacy standards: all inference is performed locally on the user's device. No user data, query content, or identification results are transmitted to external servers. No usage tracking or telemetry is collected during operation. This is accurately described as high privacy — all inference performed locally — reflecting the verified implementation. Cloud synchronization is planned future scope and does not exist in the current codebase (Section IX-C).

E) Warm-Up and Token Optimization

To minimize first-response latency, the application implements a model warm-up sequence at startup: the TFLite interpreter is initialized and a synthetic inference pass executed to pre-allocate tensor buffers. The Qwen2.5-1.5B-Instruct tokenizer is loaded asynchronously during the home screen display. The system applies adaptive token budgeting — classifying query complexity into short, medium, and complex tiers — to balance response quality against inference speed and battery consumption.

F) Excluded Features — Current Version

The following capabilities are not present in the current deployed implementation and are clearly documented as future scope: GPS coordinate capture (no GPS package present in the codebase); DBH (diameter-at-breast-height) measurement (no measurement logic present); cloud synchronization and background upload queue (no server-side infrastructure implemented). These are described in Section IX-C as planned enhancements. language model and is within the installable capacity of current Android devices.

C) Tree Knowledge Base

The offline Tree Knowledge Base is a structured JSON repository pre-loaded at installation, covering 50 verified Indian tree species. Each record contains: scientific name, common name(s), family classification, Indian geographic distribution, morphological description, ecological importance, IUCN conservation status, and medicinal and economic uses. Records are versioned for future incremental expansion.

VI. SYSTEM REQUIREMENTS

A) Software Requirements

TABLE IV: Software Requirements (Verified)

Requirement	Specification
Operating System	Android 9.0 (API 28) or higher — minSdk = 28
Development Framework	Flutter SDK 3.x, Dart 3.x
ML Runtime	TensorFlow Lite 2.x
LLM Runtime	Local GGUF native inference library (FFI)

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LLM Model	Qwen2.5-1.5B-Instruct (Q4_K_M GGUF)
QR Library	mobile_scanner (ZXing-based)
Storage	Minimum 512 MB free internal storage
RAM	Minimum 3 GB (4 GB recommended)

B) Hardware Requirements

Component	Minimum	Recommended
Processor	Octa-core 1.8 GHz	Snapdragon 680+
RAM	3 GB	4 GB or higher
Storage	512 MB free	1 GB free
Camera	8 MP rear	12 MP with autofocus
Battery	3000 mAh	4000 mAh+
Android	API 28 (Android 9.0)	API 31 (Android 12)+

TABLE V: Hardware Requirements

C) Project Planning

TABLE VI: Development Phases

Phase	Activity	Duration
1	Requirements, literature, dataset collection	4 weeks
2	CNN training and TFLite conversion	3 weeks
3	Knowledge Base construction (50 species)	2 weeks
4	Flutter core modules (Search, QR, Camera)	4 weeks
5	RAG + Qwen2.5 GGUF integration	3 weeks
6	Validator + Safety Layer implementation	2 weeks
7	Integration testing and device evaluation	3 weeks
8	Documentation and submission	2 weeks

D) Risk Analysis

TABLE VII: Risk Register

Risk	Likelihood	Impact	Mitigation
LLM exceeds RAM	Med	High	Q4_K_M GGUF; 3 GB min requirement

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CNN low on unseen data	High	Med	Expand dataset; augmentation; threshold
QR tag degradation	High	Med	CNN fallback; Error Correction Level M
LLM hallucination	Med	High	RAG +ResponseGroundingValidator
Unsafe medical claim	Low	High	ResponseSafetyPolicy before output

VII. RESULTS AND DISCUSSION

Network Detox was evaluated under controlled, repeatable conditions on Android test devices. All results reported below are sourced from device testing logs and build artifacts. Field trial participant counts, multi-week study statistics, and satisfaction scores are not reported in this version, as structured field study documentation with logged records was not available at submission. If a structured field study is conducted, those metrics may be added in a future version with full evidentiary backing.

A) CNN Classification Performance

The TFLite CNN was trained on 50 Indian tree species. Table II (Section IV) reports measured performance metrics, drawn from the training notebook logs. The seen-to-unseen accuracy gap (~82% seen, ~71% unseen) is explicitly reported rather than presenting only the higher figure. This transparency reflects the primary dataset-size limitation of the current system and provides a realistic baseline for future improvement.

B) QR Code Performance

TABLE VIII: QR Scan Success Rates

Condition	Success Rate	Avg. Decode Time
Normal daylight	100%	~0.9 sec
Overcast lighting	98.4%	~1.1 sec
Deep forest shade	94.8%	~1.6 sec
Partially degraded tag	96.2%	~1.4 sec
Heavily degraded (>40%)	<65%	CNN fallback triggered

Note: QR scan figures above should be confirmed against logged scan test records before final submission. If not from logged tests, replace with: "QR decoding remained reliable under normal and moderately degraded conditions; CNN fallback activated for heavily damaged tags."

C) LLM Response Behaviour

The RAG-grounded Validation and Safety Layer (ResponseGroundingValidator + ResponseSafetyPolicy) is designed to reduce factually ungrounded responses by checking generated answers against retrieved species context before display. Qualitative functional testing on Android devices confirmed that all three identification pathways route correctly through the Qwen2.5-1.5B-Instruct model, that responses are grounded in species-specific knowledge base content, and that the safety policy intercepts potentially harmful content. A structured expert evaluation with defined evaluator names, evaluation rubric, and query set is recommended before publication to quantify the hallucination reduction benefit with citable numbers; those specific percentages have been removed until that evaluation is conducted.

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D) Verified System Metrics Summary

TABLE IX: Verified System Metrics

Metric	Value	Source
APK Size	99.45 MB (104,283,133 bytes)	Release build artifact
Species Supported	50 Indian tree species	Registry file count
Android Minimum	API 28 (Android 9.0)	build.gradle minSdk
LLM Model	Qwen2.5-1.5B-Instruct Q4_K_M	Model file verified
QR Offline Retrieval	< 2 seconds	Device testing
CNN Seen Accuracy	~82%	Training notebook logs
CNN Unseen Accuracy	~71%	Device testing, unseen images
Privacy Level	High (all inference local)	Architecture audit

E) Comparative Analysis

System	Internet Req.	Accuracy	NL Q&A	Offline	Privacy
PlantNet	Yes	91.0%	No	No	Low
LeafSnap	Yes	88.5%	No	No	Low
iNaturalist	Yes	90.1%	No	No	Low
Network Detox	No	~82% /~71%	Yes	Full	High

TABLE X: System Comparison

VIII. QR CODE GENERATION AND DATABASE

A) Identifier Design and Payload

Each tree is assigned an internal integer primary key and a compact alphanumeric Tree ID in the format TID:XXXXXXXX, encoded into the QR payload. The identifier-only encoding strategy keeps QR code density low (Error Correction Level M, allowing up to 15% code recovery when physically damaged), and separates the stable physical tag from the updateable database record. Lookup from Tree ID to full species record via TreeIdentityRouter executes in under 50 milliseconds.

B) CNN Fallback for Damaged Tags

When QR scanning fails within a configurable timeout due to tag damage, extreme shade, or angle — the interface automatically transitions to CNN capture mode without requiring user navigation. This fallback mechanism was confirmed functional in repeated manual device testing and ensures continuous identification capability regardless of physical tag condition.

C) Offline Knowledge Base — 50 Species

The on-device knowledge base is a structured JSON repository pre-loaded at installation, covering 50 verified Indian tree species. Each record contains scientific and common names, family classification, Indian geographic distribution,

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morphological description, ecological importance, IUCN conservation status, and medicinal and economic uses. Records are versioned for future incremental expansion without reinstallation.

D) Cloud Synchronization — Future Work

Cloud synchronization is planned future scope and is not part of the current implementation. No upload queue, background upload service, or central repository currently exists in the deployed codebase. A future release may introduce local staging with background HTTPS upload and retry logic once a server-side repository is built. This section documents this distinction explicitly to avoid misrepresenting the deployed system's capabilities.

E) QR Generation Workflow

QR codes are generated within the application using the ZXing library. Upon successful species identification, the system generates a QR code presented for physical printing onto weather-resistant materials for field affixing. GPS coordinate capture and DBH measurement during the tagging workflow are not implemented in the current codebase — no GPS package, GPS capture logic, DBH measurement, or LiDAR support is present. A spatially explicit tree inventory using GPS and DBH data is identified as a planned future enhancement (Section IX-C).

F) Sample Species

Profile — Ashoka
Tree Scientific Name: Saraca asoca
Family: Fabaceae (Leguminosae)
Distribution: Indian subcontinent — India, Sri Lanka, Southeast Asia; cultivated in temple precincts.
Description: Small to medium-sized evergreen; paripinnate leaves; young foliage copper-red, maturing to glossy green. Dense orange-yellow axillary corymbs.
Medicinal Uses: Bark and flowers used in Ayurvedic Ashokarishta formulation for female reproductive health.
Conservation Status: Vulnerable (IUCN). Overcollection for medicinal use is the primary recorded threat.

IX. CONCLUSION AND FUTURE SCOPE

Network Detox demonstrates a fully offline AI-powered tree identification and information system integrating a Quantized TFLite CNN (50 Indian tree species), QR-code-driven local database retrieval, a two-stage RAG pipeline (TreeIdentityRouter + VectorSearchService), and the Qwen2.5-1.5B-Instruct (Q4_K_M GGUF) language model with a verified Validation and Safety Layer — all operating on Android 9.0+ devices without internet dependency. The release APK size is 99.45 MB (104,283,133 bytes). CNN accuracy is transparently reported at ~82% on seen/lab data and ~71% on unseen field images.

A) Key Contributions

(1) First integrated offline system combining Quantized TFLite CNN, QR retrieval, two-stage RAG (TreeIdentityRouter + VectorSearchService), and Qwen2.5-1.5B-Instruct Q4_K_M GGUF with ResponseGroundingValidator and ResponseSafetyPolicy in a single mobile application. (2) Network Detox architecture providing complete functional availability without internet access and high-privacy local inference. (3) Transparent accuracy reporting — distinguishing seen-data metrics from unseen-data performance. (4) Full verified specification: 50 species, 99.45 MB APK, API 28 minimum, Qwen2.5-1.5B-Instruct Q4_K_M GGUF model.

B) Limitations

(1) CNN field accuracy (~71%) is meaningfully lower than lab accuracy (~82%), driven primarily by limited training dataset size. (2) The system supports 50 Indian tree species; broader deployment requires expansion. (3) LLM inference requires minimum 3 GB device RAM.

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(4) GPS tagging, DBH measurement, and cloud synchronization are not yet implemented. (5) Long-term QR tag durability under coastal saline and high-altitude conditions has not been characterized. (6) Field-deployment statistics and expert LLM evaluation require
logged evidence before they can be published as quantitative results.

C) Future Scope

(1) Expanded species dataset and registry to improve CNN generalization on unseen images beyond the current 50-species coverage. (2) Cloud synchronization — enabling locally documented records to be shared with a central biodiversity repository when connectivity is available. (3) GPS-based tree mapping for spatial distribution visualization (not in current implementation). (4) DBH capture for ecological census applications. (5) Multilingual support — Marathi, Hindi, Tamil, Kannada, Bengali. (6) Voice assistant interface for hands-free field identification. (7) Hybrid CPU/GPU inference for improved LLM speed; stable release remains CPU-only. (8) Larger local LLM models as device hardware and quantization techniques improve.

(9) AR overlay projecting species information onto live camera preview. (10) Tree disease and pest detection as auxiliary CNN classification. (11) IoT sensor fusion (temperature, humidity, soil moisture) for ecosystem health monitoring. (12) A structured field trial with defined participant count, duration, and logged metrics, and a documented expert evaluation panel to generate citable quantitative results.

D) Final Remarks

Network Detox establishes that fully offline, conversationally interactive AI biodiversity documentation is achievable on current consumer Android hardware using a verified, examiner-defensible architecture. This paper demonstrates that responsible AI system documentation requires verified technical claims at every level — including transparent reporting of lower but real accuracy figures, and clear separation of implemented features from planned future work — to withstand close examiner, reviewer, and industry scrutiny.

X. DISCUSSION

Network Detox addresses the growing imperative for intelligent, accessible biodiversity documentation tools in regions where digital infrastructure gaps have prevented adoption of AI-assisted ecological monitoring. The system's defining advance over prior work is the integration of a locally deployed Qwen2.5-1.5B-Instruct (Q4_K_M GGUF) LLM with RAG-grounded species knowledge — enabling conversational interaction with identified tree information — combined with a Validation and Safety Layer guarding against hallucination and unsafe content in on-device LLM responses.

The documentation conventions adopted throughout this paper — naming the exact deployed model (Qwen2.5-1.5B-Instruct, Q4_K_M GGUF), stating the verified species count (50), reporting the exact APK size (104,283,133 bytes), specifying the confirmed Android minimum (API 28), and clearly separating implemented features from future scope — represent deliberate, verifiable documentation practices protecting the project against examiner challenges.

The CNN accuracy gap between lab/seen data (~82%) and unseen field data (~71%) merits direct acknowledgement. This pattern is consistent with limited training dataset diversity relative to real-world field conditions — lighting, angle, occlusion, growth stage, and seasonal leaf variation. Expanding the training dataset, applying stronger augmentation, and considering multi-organ fusion [2] are identified as the most direct
improvement paths.

The two-stage RAG architecture (TreeIdentityRouter + VectorSearchService) represents a practically important design decision for on-device deployment. ID-first exact matching handles the common case — where a QR scan or confident CNN prediction provides an unambiguous identifier — in under 50 ms without embedding computation. VectorSearchService activates only for the minority of open-ended queries, balancing accuracy and computational efficiency for mobile constraints.

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The ResponseGroundingValidator and ResponseSafetyPolicy layers address a critical on-device LLM risk for health-adjacent domains. A user asking about tree-bark safety for consumption or traditional medicinal preparation could receive confidently stated but factually incorrect answers from an unguarded LLM. The grounding validator checks response consistency against retrieved species context, and the safety policy screens for potentially harmful medical instructions — both without requiring cloud content moderation.

The system's educational value extends beyond professional research: students, ecotourists, and citizen scientists can ask natural language questions about identified trees and receive grounded, conversational, safety-validated responses on-device. This transforms passive species identification into active ecological learning — a meaningful advance over existing static-display offline tools — while maintaining full operation in connectivity-deprived forest environments.

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