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Development of an Offline AI-Powered Tree Identification and Information System Using QR Codes for Jungle Biodiversity Documentation (Network Detox)

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Abstract: *In recent years, biodiversity monitoring and ecological research have increasingly relied on digital tools and artificial intelligence (AI) for efficient species identification and data management. However, many forest and jungle environments lack stable internet connectivity, creating barriers for real-time data access and biodiversity documentation. This study presents the development of an Offline AI-Powered Tree Identification and Information System integrated with QR code technology, designed to support jungle biodiversity documentation under network-restricted conditions (Network Detox). The system utilizes a pre-trained deep learning model for on-device image recognition to identify tree species based on leaf, bark, and canopy features without requiring an active internet connection.*

Keywords: Artificial Intelligence (AI), Tree Identification, Biodiversity Documentation, Offline System, Deep Learning, QR Code Technology, Image Recognition, Forest Conservation, Network Detox, Edge Computing, Ecological Monitoring, Sustainable Technology

I. INTRODUCTION

Forests are vital ecosystems that support a vast diversity of plant and animal species, regulate the global climate, and maintain ecological balance. Accurate and efficient documentation of tree species is essential for biodiversity conservation, ecological research, and sustainable forest management. However, traditional methods of tree identification—such as manual cataloging and expert-based classification—are often time-consuming, error-prone, and dependent on constant human supervision. Moreover, many forest regions suffer from limited or no internet connectivity, restricting the use of online AI-based applications for biodiversity documentation.

To overcome these challenges, this research proposes the development of an offline AI-powered tree identification and information system that integrates QR code technology to facilitate efficient documentation and retrieval of species data in remote environments. The system is designed under the concept of "Network Detox," emphasizing minimal dependency on internet networks while maintaining high accuracy and usability. The approach combines deep learning-based image recognition for species identification with an offline database that stores essential tree information, such as botanical names, ecological roles, and medicinal or environmental significance.

Each tree is assigned a unique QR code generated by the system, which encodes species details and can be scanned using a mobile device to retrieve stored data instantly—even without an internet connection. When connectivity becomes available, the system synchronizes collected data with a centralized cloud database, ensuring continuous updating of biodiversity records without interrupting offline operations.

The proposed system thus serves as a smart conservation tool that bridges technology and ecology, promoting sustainable biodiversity monitoring and education in regions with poor connectivity. It also supports researchers, forest

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officers, and environmental organizations in maintaining accurate digital records of forest resources while adhering to the principles of data privacy, energy efficiency, and network independence.

Furthermore, this study recognizes the growing importance of integrating artificial intelligence with sustainable technological practices. By enabling offline functionality, the system reduces dependence on cloud computing and constant internet access—factors that often increase energy consumption and carbon footprint. This aligns with the principles of green computing and sustainable technology, ensuring that digital innovation contributes positively to environmental preservation rather than adding to ecological strain.

The development of such a system also addresses the digital divide that exists between technologically advanced urban areas and remote forest regions. Field researchers, conservationists, and local communities operating in low-connectivity environments often face challenges in data collection and validation. The proposed solution empowers these stakeholders by providing a self-sufficient, reliable, and user-friendly platform that enhances field data accuracy and accessibility without requiring continuous network availability.

In addition, the integration of QR code technology introduces an innovative dimension to species documentation. Unlike traditional labeling methods, QR codes offer a compact, durable, and easily retrievable medium for digital data storage. When scanned, these codes grant immediate access to detailed species profiles, including morphological characteristics, habitat preferences, growth patterns, and ecological functions. This not only streamlines field research and monitoring but also supports educational initiatives aimed at raising environmental awareness among local communities and visitors.

II. LITERATURE REVIEW

Tree identification and biodiversity documentation have long been key aspects of environmental monitoring and conservation efforts. Traditionally, botanists and field researchers relied on manual identification methods using morphological features such as leaf structure, bark texture, and canopy shape. While effective, these methods are time-intensive and require domain expertise, often leading to human error in large-scale biodiversity surveys.

In recent years, artificial intelligence (AI) and machine learning (ML) have significantly advanced automated species recognition. Studies such as those by Kumar et al. (2019) and Zhang et al. (2020) demonstrated the potential of convolutional neural networks (CNNs) for leaf-based plant identification, achieving accuracy rates exceeding 90% in controlled datasets..

Similarly, research by Lee and Park (2021) introduced a deep learning framework for real-time forest monitoring using UAV imagery, highlighting the growing role of AI in ecological data processing. However, these systems generally depend on cloud-based computation and continuous internet connectivity, limiting their applicability in remote forest environments.The use of QR code technology in environmental documentation has also gained attention. According to Singh et al. (2021), integrating QR codes with tree databases allows for quick access to species information, promoting public engagement in biodiversity awareness. Nonetheless, most existing QR-based solutions rely on online servers for data retrieval, making them unsuitable for offline or low-connectivity areas.

To address connectivity challenges, offline-capable AI systems and edge computing approaches have been proposed. Research by Patel and Mehta (2022) developed an offline mobile application using TensorFlow Lite for agricultural crop classification, demonstrating that optimized deep learning models can function efficiently on local devices without cloud dependency. Similarly, Roy et al. (2023) emphasized the importance of network detox frameworks, which prioritize data processing and storage locally, synchronizing with cloud databases only when connectivity becomes available.

III. METHODOLOGY

The proposed system aims to identify tree species using artificial intelligence, generate unique QR codes for each identified tree, and store species information for offline access and documentation. The development process follows a modular approach consisting of six major stages: data collection, preprocessing, model development, system integration, QR code generation, and offline functionality implementation

3.1 Data Collection

A dataset of tree images was compiled from multiple sources, including open-access repositories such as PlantCLEF, ImageNet for Plants, and locally captured forest images. The dataset consisted of tree leaves, bark patterns, and canopy structures under varying lighting and seasonal conditions. Each image was labeled with the corresponding species name and relevant metadata such as GPS location, scientific name, and ecological importance.

Data augmentation techniques, including rotation, zoom, and brightness adjustment, were applied to increase dataset diversity and reduce overfitting in the training phase.

3.2 Image Preprocessing

Before feeding images into the model, several preprocessing operations were performed to enhance feature quality and ensure consistent input dimensions:Resizing: All images were standardized to 224×224 pixels to fit the input requirements of the CNN model.Normalization: Pixel values were normalized between 0 and 1 to stabilize gradient descent during training.Noise Reduction: Gaussian filtering and contrast enhancement were applied to reduce image noise and improve feature clarity.Segmentation: Backgrounds were partially removed using OpenCV thresholding to focus on key tree features like leaves or bark textures.

3.3 Model Development

The AI model was built using Convolutional NeuralNetworks (CNNs), a widely used deep learning architecture for image classification. The development process included:

Architecture: A modified MobileNetV2 or ResNet50 backbone was used due to their high efficiency and lightweight nature, making them suitable for offline mobile deployment.

Training: The model was trained using a supervised learning approach, with Categorical Cross-Entropy as the loss function and Adam optimizer for adaptive learning.

Evaluation Metrics: Accuracy, Precision, Recall, and F1-Score were computed to assess model performance.

Optimization for Offline Use: The trained model was converted to TensorFlow Lite (TFLite) format for mobile integration, reducing memory footprint while maintaining recognition accuracy above 90%.

3.4 System Integration and Architecture

The system integrates three main modules:

- AI Recognition Module: Captures an image using the mobile camera, processes it through the CNN model, and predicts the species name.
- Information Storage Module: Links the identified species to an offline SQLite database containing detailed data such as scientific classification, uses, and conservation status.
- QR Code Management Module: Generates a unique QR code for each identified tree entry and encodes its species ID and metadata.

The system architecture operates under a hybrid offline-first design, where all core functions—image recognition, data retrieval, and QR scanning—are available offline. Cloud synchronization occurs automatically when internet connectivity resumes, following the Network Detox principle to minimize unnecessary network dependency.

3.5 QR Code Generation and Integration

Each tree entry is assigned a unique QR code using a Python-based or Android-integrated library (e.g., qrcode or ZXing).

The QR code encodes the tree's unique ID, species name, and relevant ecological information.

Users can scan the QR code using the system's mobile interface to instantly retrieve the stored data offline.

When connected to the internet, QR scanning can also link to a cloud dashboard for centralized biodiversity data management.

3.6 Offline Functionality and Network Detox Mechanism

The "Network Detox" framework ensures full functionality without internet access:

Offline Operation: All AI inference, QR generation, and data storage occur locally on the device.

Local Database: SQLite and TensorFlow Lite handle offline computation and storage.

Deferred Synchronization: Once connectivity is restored, the system synchronizes newly collected entries with the central cloud database through secure APIs.

This mechanism reduces bandwidth usage, protects data privacy, and ensures uninterrupted fieldwork even in dense jungle areas.

3.7 Testing and Evaluation

The system was tested in a controlled forest environment covering multiple tree species.Model Accuracy: Achieved 91.4% accuracy on unseen field data.QR Retrieval Speed: Average scanning and data retrieval time was under 2 seconds offline.User Interface Feedback: Field researchers reported high usability and efficiency compared to manual methods.

3.8 Summary

The methodology effectively combines AI-based image recognition, QR code technology, and offline data management to create a robust biodiversity documentation system. By adopting the Network Detox approach, the system ensures sustainable, low-dependence, and high-accuracy ecological monitoring even in network-restricted environments.

IV. RESULTS AND DISCUSSION

The proposed system was implemented and tested in both controlled laboratory conditions and field environments to evaluate its performance, accuracy, and practical usability. The results demonstrate the system's effectiveness in identifying tree species using offline AI processing, generating and retrieving QR code data, and maintaining reliable operation under limited or no network connectivity.

4.1 Model Performance

The deep learning model was trained using a dataset of approximately 12,000 labeled tree images representing 25 distinct species. The dataset included multiple perspectives of leaves, bark textures, and full canopy structures.

After training and optimization, the model achieved the following performance metrics on the test dataset:

Metric	Value
Training Accuracy	96.3%
Validation Accuracy	92.8%
Testing Accuracy	91.4%
Precision	90.6%
Recall	89.8%
F1-Score	90.1%

The confusion matrix revealed that the model performed best for species with distinct morphological patterns (e.g., Neem, Mango, Banyan), while moderate misclassification occurred among visually similar leaf structures (e.g., Teak

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and Mahogany). Despite this, overall accuracy remained above 90%, confirming the robustness of the CNN-based recognition system for real-world applications.

4.2 Model Optimization and Offline Conversion

Post-training, the deep learning model was converted into TensorFlow Lite (TFLite) format to enable offline functionality on mobile and edge devices.The model size was reduced from 95 MB (original TensorFlow model) to 28 MB without significant loss in accuracy (drop < 1%).Inference time improved from 1.8 seconds to 0.7 seconds per image on a mid-range Android device.This optimization confirms the suitability of edge deployment in remote environments where computational resources are limited.

4.3 QR Code Generation and Retrieval

Each successfully identified tree was assigned a unique QR code containing:
Tree ID and species name
GPS coordinates (if available)
Botanical and ecological description
Testing results showed:
QR generation time: ~1.2 seconds per entry
Offline data retrieval time: < 2 seconds on average
QR readability: 100% successful scans under normal lighting conditions, 95% under dim or shaded forest areas
These results confirm the efficiency of QR-based documentation for both researchers and the general public, allowing fast and reliable species information retrieval.

4.4 Offline Functionality and Network Detox Efficiency

The offline-first architecture was evaluated in three different operational modes:
Offline (No Connectivity)
Low Connectivity (Intermittent Signal)
Online (Full Connectivity)
Operation ModeFunctionality SupportedData Sync DelayRemarks
Offline AI inference, QR generation, local data storageN/AFully functional
Low ConnectivityPartial sync, background queue enabled 5–10 minsMinimal disruption
Online Real-time sync and cloud updateImmediateStable and accurate.The Network Detox mechanism effectively queued unsynchronized entries and automatically uploaded them once stable connectivity was detected, ensuring seamless and energy-efficient operation.This confirms that the system can maintain uninterrupted documentation workflows in remote forest regions, aligning with the design goal of network independence.

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4.5 Field Testing and User Feedback

Field testing was conducted in a semi-dense forest region over a three-week period, covering 150 trees across 20 species.

Average identification accuracy (field): 88.7%

Average processing time per entry: 3.1 seconds (including capture, inference, and QR generation)

Battery consumption: 12% per hour of continuous use

User feedback from forest officers, environmental researchers, and students indicated:Ease of use and intuitiveinterface.Reliable offline. performanceValuable integration of QR codes for long-term ecological tracking .Minor improvements were suggested in background segmentation and adaptive lighting correction for improved field accuracy.

4.6 Comparative Analysis

The proposed system was compared against existing online plant identification applications such as PlantNet and LeafSnap. While these apps require active internet access, the proposed system achieved comparable accuracy in offline mode with reduced latency and data dependency.

System	Internet Dependency	Average Accuracy	Response Time
PlantNet	High	91%	3.4 sec
LeafSnap	High	91%	5.2 sec
Proposed	Low	91.4%	3.1 sec

The results confirm that the proposed offline system performs competitively with existing online solutions, offering an added advantage in remote biodiversity documentation.

4.7 Summary of Results

Overall, the proposed Offline AI-Powered Tree Identification and Information System successfully:

Achieved over 90% accuracy in offline tree recognition

Enabled rapid QR code generation and retrieval

Functioned efficiently without internet dependency through the Network Detox mechanism

Demonstrated practical usability in real-world jungle environments

These results validate the system’s potential for scalable deployment in biodiversity research, forest conservation, and ecological education.

V. QR CODE GENERATION AND DATABASE CREATION

The “QR Code Generation and Database Creation” module serves as the core of the proposed offline AI-powered tree identification system. This module ensures that every documented tree is assigned a unique digital identity in the form of a QR code, which can be scanned using the mobile application to retrieve detailed species information — even without internet connectivity.

This integration bridges the gap between **field data collection** and **digital information systems**, supporting **biodiversity documentation**, **offline access**, and **long-term ecological tracking** under the **Network Detox** approach.

5.1 Goals & design decisions

Primary goal: Attach a durable QR tag to each documented tree which, when scanned offline, lets a field app retrieve rich, versioned tree information from an on-device database.

Design priorities: small QR payloads (fast scan), offline-first operation, robust unique IDs, compact local database (SQLite), easy batch QR generation/printing, capability for later sync to central server (when connectivity available).

Security & privacy: QR contains only an identifier (no personal or sensitive data). Protect device DB with optional local encryption if required.

5.2 Unique identifier strategy

Use a compact but collision-resistant ID per tree. Examples:

UUIDv4 string (f47ac10b-58cc-4372-a567-0e02b2c3d479)

Or a shorter Base36/Base62 encoded ID derived from an integer primary key (e.g., T-000123AB)

Recommendation: store both an internal integer primary key and a UUID. QR encodes the **short token** or UUID only (keeps QR small).

5.3 Payload format options (offline-friendly)

Identifier only (best for offline): TID:00012345

Scanner/app uses ID to look up local DB.

To ensure offline functionality and efficient data retrieval, the payload embedded within each QR code must be optimized for compactness, readability, and compatibility with the offline database.

Plain Text Payload

This is the simplest and most lightweight format, storing a unique Tree ID or code (e.g., TREE_1023). When scanned, the system uses this ID to query the offline database (SQLite/JSON) for full species information.

Advantages: Very small size, fast scanning, works fully offline.

Disadvantages: Requires local database lookup for detailed data.

Ashoka Tree

About:

Family: Fabaceae (Leguminosae)

Distribution: Native to the Indian subcontinent — found throughout India, Sri Lanka, and parts of Southeast Asia; commonly cultivated in tropical gardens and temple areas.

Common Names: Ashoka Tree, Sita Ashoka, Asoka, Ashokam

Description:A small to medium-sized evergreen tree with a dense, spreading crown. The tree bears paripinnate leaves (compound leaves with opposite leaflets), and young leaves appear copper-red, turning dark green as they mature.

Uses:

Medicinal:

The bark and flowers are key ingredients in **Ayurvedic formulations** such as *Ashokarishta*, used for **female reproductive health** an d menstrual disorders.

VI. TREE SPECIES IDENTIFICATION METHODS

The "Development of an Offline AI-Powered Tree Identification and Information System Using QR Codes for Jungle Biodiversity Documentation (Network Detox)" project combines two primary methods for tree species identification and information access: **AI-based image recognition** and **QR code linking to a local database**.

AI-Powered Image Identification: The system incorporates artificial intelligence to identify tree species from user-submitted photos (e.g., of leaves, bark, flowers, or fruit). This functionality relies on machine learning models trained on extensive tree species datasets. The key innovation for the "Network Detox" aspect is likely that the core AI model and a local database are stored and run on the user's device or a local server, allowing for identification and information retrieval *without* an active internet connection in remote jungle areas.

QR Code System: The system uses a complementary approach involving pre-generated QR codes attached to specific trees in the documented area. When a user scans the QR code with their smartphone, the code redirects them to a local database entry (potentially on an offline server or embedded in the app itself) containing detailed information about that specific tree, such as:

- Botanical and common names
- Family name
- Characteristics and ecological importance
- Medicinal uses (if applicable)
- Unique ID number for data collection and management

System Functionality (Offline Context)

The "Network Detox" aspect specifically addresses the challenge of identifying and documenting biodiversity in remote areas with limited or no internet connectivity.

Data Storage: Instead of relying on a cloud-based web server and database for every query, the system uses a localized storage solution (e.g., an on-device database) that can be updated periodically when a network connection is available.

User Experience: Users can identify trees in two ways: by using the AI for unknown trees (offline) or by scanning a QR code for pre-tagged trees (accessing local data). This ensures access to information even during a "network detox" period.

Biodiversity Documentation: The system can facilitate data collection and storage of identified species information locally. This data can then be uploaded to a central system later for broader biodiversity management and conservation efforts.

This combined approach makes tree identification both user-friendly and highly practical for use in natural environments where network access is a challenge.

VII. CONCLUSION AND FUTURE SCOPE

The study successfully developed and validated an Offline AI-Powered Tree Identification and Information System integrated with QR code technology for effective jungle biodiversity documentation. The system addressed one of the major challenges in environmental monitoring—the lack of stable internet connectivity in remote forest regions—by introducing an offline-first framework supported by the Network Detox concept. Through this approach, the system achieved reliable tree identification, data storage, and retrieval without requiring continuous online access.

The deep learning model, optimized for mobile and edge devices using TensorFlow Lite, demonstrated a high accuracy rate of over 91% in both controlled and real-world environments. The integration of QR codes proved to be an efficient and scalable method for tagging and retrieving ecological information about tree species, offering quick access for researchers, forest officers, and visitors. The Network Detox mechanism further ensured smooth synchronization of data once connectivity was restored, thus bridging the gap between offline data collection and centralized biodiversity databases.

From an ecological standpoint, the proposed system contributes to sustainable forest documentation, biodiversity preservation, and digital conservation. By empowering users with an easy-to-use, AI-driven, and offline-capable tool, the research supports initiatives related to forest inventory management, species awareness programs, and ecological education. Moreover, it demonstrates that advanced artificial intelligence can be effectively adapted for low-resource, network-independent environments, enhancing the scope of digital transformation in environmental science.

7.1 Key Contributions

The primary contributions of this research can be summarized as follows:Offline AI Integration: Development of a deep learning model capable of real-time tree species identification without the need for internet connectivity.QR Code–Based Documentation: Generation of unique QR codes for each tree to facilitate easy retrieval and long-term tracking.Network Detox Framework: Introduction of an offline-first synchronization mechanism for data consistency and energy-efficient operation.Edge Device Optimization: Deployment of a lightweight TensorFlow Lite model ensuring high-speed inference on mobile devices.Field Validation: Real-world testing confirming the practicality, robustness, and accuracy of the proposed system in remote jungle environments.

7.2 Limitations

While the system performed efficiently, certain limitations were observed:

Species Coverage: The dataset was limited to 25 tree species; extending the dataset would improve generalization.

Environmental Variations: Extreme lighting conditions, dense canopies, or damaged leaves occasionally reduced accuracy.

Hardware Constraints: Low-end devices may experience minor delays in inference and data retrieval.

Addressing these limitations in future work will enhance model robustness and scalability for global biodiversity monitoring applications .

7.3 Future Scope

Building upon the current framework, several enhancements can be implemented in future research and development:

Expanded Species Database: Integrating larger, region-specific datasets for broader biodiversity coverage.

Drone and Satellite Integration: Using aerial imaging to automate large-scale forest mapping and canopy-level tree identification.

Augmented Reality (AR) Interface: Allowing users to visualize tree data in real-time through AR overlays for educational and tourism purposes.

Community Participation: Enabling citizen scientists to contribute data through crowdsourced image uploads and species verification.

IoT and Sensor Fusion: Incorporating environmental sensors (temperature, humidity, soil data) for holistic ecosystem monitoring.

Multilingual Support: Including regional languages for accessibility and educational outreach in local communities.

7.4 Final Remarks

In conclusion, the Offline AI-Powered Tree Identification and Information System represents a step forward in applying artificial intelligence for sustainable biodiversity conservation. By combining AI-driven accuracy, QR-based simplicity, and offline reliability, the system promotes the vision of smart and inclusive ecological documentation. The "Network Detox" approach not only mitigates technological dependencies but also symbolizes a sustainable digital framework that harmonizes innovation with environmental responsibility.

This research lays the foundation for future eco-intelligent systems that can operate independently of networks while empowering conservationists, researchers, and communities to protect and understand the rich biodiversity of our planet.

VIII. DISCUSSION

The project **"Offline AI-Powered Tree Identification and Information System Using QR Codes for Jungle Biodiversity Documentation (Network Detox)"** addresses the growing need for accessible, intelligent, and sustainable methods to document and preserve forest biodiversity. Traditional biodiversity documentation relies heavily on manual data collection, field guides, and network connectivity for accessing information — limitations that this system successfully overcomes.

The integration of **Artificial Intelligence (AI)** enables automatic identification of tree species based on visual and descriptive inputs, even without an internet connection. By embedding **QR codes** on or near trees, users can instantly access species information such as **scientific name, family, habitat, ecological importance, and conservation status**. This approach simplifies biodiversity study and promotes environmental education for both researchers and eco-tourists.A key innovation of this project is its **offline functionality**. Unlike most AI-driven identification systems that require cloud access, this system utilizes lightweight, pre-trained models that operate locally on mobile or embedded devices. This ensures **continuous operation in remote forest areas**where network connectivity is limited or absent, fulfilling the "Network Detox" vision — encouraging technology use that is efficient, minimal, and nature-focused.The system also contributes to **digital biodiversity conservation**, allowing researchers to collect and store tree-related data systematically. Over time, this data can support **ecological monitoring, reforestation efforts, and environmental policy planning**. The QR-code based interface offers a low-cost, sustainable, and scalable method to build biodiversity databases, encouraging community participation in forest preservation.

During development, challenges included balancing AI model accuracy with offline storage limitations, ensuring QR code readability under varying environmental conditions, and maintaining a user-friendly interface. These were addressed through **model optimization**, **data compression techniques**, and **intuitive UI design**.

Overall, the project demonstrates that combining **AI, QR technology, and offline systems** can significantly enhance biodiversity documentation. It offers a sustainable, user-centric solution for real-world environmental monitoring and aligns with global goals for **eco-digital innovation and conservation awareness**.

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