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FOOTPRINTAI-I

Geo-Enhanced MobileNetV2 for Robust Classification of Partial Wildlife Tracks in Diverse Terrains

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Abstract: Traditional methods of wildlife monitoring in India encounter difficulties due to manual footprint analysis, which has trouble identifying incomplete or blurred tracks in different field conditions such as rain and uneven terrain. Current systems do not have strong deep learning capabilities suitable for edge deployment or provide clear, interpretable results for conservationists. FootPrintAI-India presents a streamlined MobileNetV2 architecture integrated with Squeeze-and-Excitation attention, reaching 85.8% validation accuracy on 2,528 images of five major Indian species: deer, elephant, leopard, tiger, and wolf. The system utilizes Test-Time Augmentation (TTA), temperature-scaled confidence calibration, GradCAM explainability, and geo-aware filtering to ensure real-world robustness, even with imperfect footprints. Built using a React frontend, FastAPI backend, and hosted on Render cloud, it provides JWT-secured batch processing, interactive maps, AI chat, and human-in-the-loop refinementfeatures specifically tailored for Indian wildlife scenarios that previous global AI footprint studies have not covered. This portable platform minimizes reliance on specialists and allows for scalable, transparent monitoring of poaching and habitat loss.

Index Terms **-** Wildlife footprint classification, MobileNetV2, Explainable AI, Geo-filtering, Conservation technology.

I. Introduction

In India, wildlife monitoring has increasingly embraced non-invasive technologies to address poaching, habitat loss, and the decline of biodiversity, although traditional footprint analysis still depends largely on manual identification by experts. This method has difficulty handling incomplete, blurred, or environmentally damaged tracks affected by rain, soil differences, and landscape features, resulting in unreliable performance and challenges in scaling up for extensive conservation initiatives. Field researchers frequently rely on subjective visual evaluations or simple imaging devices that aren't automated, which hinders the creation of consistent species distribution data for groups such as forest departments and NGOs.

Traditional wildlife tracking methods, including camera traps and acoustic monitoring, depend on centralized data storage systems that are susceptible to mistakes, incomplete records, and reduced reliability in field conditions. These constraints make it harder to resolve disputes in population estimates, decrease the clarity of monitoring efforts, and require a significant amount of manual work to analyze footprint evidence from various habitats. Although deep learning has improved image classification, many applications concentrate on global datasets or controlled lab environments, providing minimal benefit for real-time, interpretable predictions in Indian wilderness areas with limited resources.

To tackle these challenges, this paper introduces FootPrintAI-India, an AI-driven footprint intelligence system that provides clear, practical species identification for conservation professionals. It uses a MobileNetV2 architecture combined with Squeeze-and-Excitation attention mechanisms, predicts lifecycles through a 9-stage inference process, and incorporates Test-Time Augmentation (TTA), GradCAM for interpretability, and geo-aware filtering to effectively manage incomplete tracks. Users access immutable, visualized insights through a React-based web interface featuring JWT authentication, batch processing, interactive maps, and human-in-the-loop active learning, thereby enhancing trust and scalability in India's wildlife monitoring ecosystems.

II. EXISTING & PROPOSED SYSTEM:

EXISTING SYSTEM:

Current wildlife monitoring systems mainly depend on centralized databases operated by separate organizations or research groups, leading to disjointed tracking data and restricted overall visibility of field observations. These systems are prone to mistakes from manual footprint identification, do not allow for independent audits, and offer limited assistance in confirming species presence during real-time conservation efforts. Field researchers usually rely on subjective evaluations from experts or rudimentary imaging records that are frequently incomplete, resulting in an increased likelihood of misidentification and diminished trust in population estimates.

Additionally, collaboration among conservation stakeholderslike forest departments, NGOs, and local patrolsis often ineffective and slow because of manual data entry and isolated reporting. Although camera traps and sound monitoring are sometimes utilized, the majority of systems keep data in centralized locations, making it difficult to independently confirm its authenticity. This situation restricts transparency and makes it challenging to address inconsistencies in biodiversity surveys.

PROPOSED SYSTEM:

The suggested FootPrintAI-India system presents a strong, edge-deployable framework focused on deep learning inference, explainable AI visualization, and interactive field processes for classifying species based on their footprints. A MobileNetV2 backbone, improved with Squeeze-and-Excitation attention blocks, analyzes footprint images through a 9-stage process, providing accurate predictions using Test-Time Augmentation (TTA) and geo-aware filtering that ensures dependable performance even on incomplete or blurred tracks across various Indian landscapes.

GradCAM heatmaps offer a visual explanation of model decisions, whereas the React-based web interface with JWT authentication supports batch processing, maintains prediction history, features interactive maps, and allows for human-in-the-loop active learning to enhance continuous improvement. Utilizing Render cloud with a FastAPI backend and SQLite storage, the platform guarantees scalability, data integrity, and easy access to actionable insightsconverting raw footprint evidence into reliable, practical conservation intelligence for researchers and patrol teams.

III. RELATED WORKS:

In-depth studies have investigated non-invasive methods for wildlife monitoring using digital technologies, especially computer vision for identifying species. Traditional wildlife tracking methods primarily rely on camera traps, acoustic sensors, and manual field surveys, which are archived in centralized databases or research platforms to record animal presence and movement. Although these systems aid in basic coordination among conservation teams, they usually do not have tamper-proof records or independent verification. This leads to ongoing challenges such as misidentifying species, inconsistencies in data, and restricted ability to audit biodiversity evaluations.

Advancements in deep learning have become a promising approach for improving the accuracy of wildlife detection, enabling automated analysis of visual indicators like footprints, fur patterns, and behavioral characteristics. Research shows that convolutional neural networks (CNNs) facilitate accurate species identification from field images, minimizing human bias and promoting collaboration among multiple stakeholders in remote environments without the need for trusted intermediaries. Applications in worldwide conservation, including African savannas, Amazon rainforests, and Asian ecosystems, demonstrate the effectiveness of CNN in preventing poaching and monitoring populations. However, many implementations focus on training backend models using clean datasets while neglecting real-world usability, which results in outputs that are difficult for non-expert rangers to understand when interpreting complex predictions.

Recent studies have incorporated explainable AI (XAI) methods, such as GradCAM, into environmental monitoring to illustrate model decisions, along with efficient architectures like MobileNet for edge devices. These AI systems analyze extensive field datasets to generate useful insights on animal distributions, but they frequently rely on centralized cloud storage that lacks provenance assurances. Few studies investigate XAI as an interpretability layer that translates raw neural activationsgenerally abstract heatmapsinto clear explanations for field personnel. Additionally, although image-based tracking through mobile applications has become popular as a connection between tangible evidence and digital records, most depend on private servers that do not have verifiable authenticity. Even when combined, CNN-XAI methods yield results that are technically complex and difficult for non-technical users to understand. As a result, there is still a gap in integrated platforms that incorporate strong footprint classification, geo-contextual filtering, active learning workflows, and deployment-ready interfaces designed for wildlife situations in India with limited resources. FootPrintAI-India tackles this issue by providing a comprehensive architecture that enhances transparency in monitoring, improves the accuracy of predictions, and increases usability for conservation professionals.

IV. METHODOLOGY

The FootPrintAI-India system is constructed using a modular and layered framework aimed at providing strong, understandable, and practical wildlife footprint classification for conservation tracking. The framework combines image preprocessing, deep learning inference, explainable AI visualization, geo-contextual validation, and interactive user workflows into a single cohesive pipeline. Every module has a distinct function within the system, guaranteeing scalability, maintainability, and dependable performance for various stakeholders, such as forest rangers, researchers, and conservation NGOs. The layered design allows for the individual improvement of components without interfering with the overall inference process or the stability of field deployment.

4.1 System Architecture Overview

FootPrintAI-India consists of several functional layers: image capture and quality evaluation, a 9-stage ML inference pipeline, generation of explainability, data storage, and a web-based analytics interface. Footprint images undergo automated validation before they are sent to the core MobileNetV2 inference engine, which is improved with Squeeze-and-Excitation attention blocks. The prediction outcomes are processed through confidence calibration, GradCAM visualization, and geo-aware filtering, leading to actionable species insights supported by visual reasoning. The system accommodates both real-time individual predictions and batch processing for extensive field datasets, with all results archived for historical review and ongoing learning improvement.

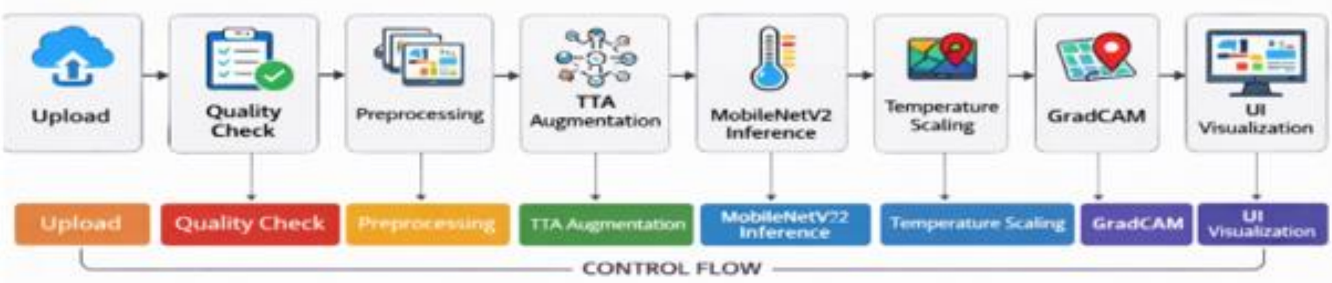

Figure 1: FootPrintAI-India *System Architecture*

4.2 Image Acquisition and Validation Module

This entry-point module manages the uploading of footprint images (both single and batch) with format validation for JPG and PNG. It also conducts automatic quality checks for blur, brightness, and completeness, as well as preprocessing tasks such as normalization and resizing to 224×224 pixels. Invalid inputs get helpful feedback, making sure that only valid field entries are processed for inference.

4.3 9-Stage ML Inference Pipeline

The core intelligence utilizes Test-Time Augmentation (TTA) across three geometric variations, extracts deep features using a MobileNetV2-SE backbone, and produces ensemble predictions. Temperature-scaled softmax calibration improves confidence scores, and the top-3 class probabilities offer context for predictions in uncertain situations.

4.4 Explainable AI and GradCAM Module

GradCAM heatmaps superimpose important areas that influence model decisions, allowing researchers to verify AI reasoning based on morphological characteristics such as the number of toes, shape of pads, and claw patterns. This visual clarity fosters confidence in automated classifications for users in the field who are not experts.

4.5 Geo-Aware Filtering and Consensus Module

Location metadata (GPS coordinates) activates prior filtering for habitat-species, minimizing false positives (e.g., tigers in grasslands dominated by elephants. Consensus validation combines TTA outputs with geographical context, highlighting low-confidence predictions (below 70%) for review by humans.

4.6 User Interface and Analytics Layer

The React-based frontend provides dynamic dashboards featuring prediction history, interactive species distribution maps, performance analytics, and AI chat support powered by Gemini. JWT-authenticated access facilitates safe collaboration among multiple users within conservation teams.

4.7 Algorithm

PROCEDURE FOOTPRINT_CLASSIFICATION(Image I, Location L)
1. Validate image format and quality metrics. 2. Apply preprocessing: resize, normalize, enhance contrast 3. Generate TTA variants: original, rotated, flipped 4. Extract features via MobileNetV2-SE backbone 5. Ensemble predictions with temperature scaling 6. Generate GradCAM heatmap for top prediction 7. Apply geo-filtering using habitat-species priors(L). 8. Compute consensus score; flag low-confidence for review 9. Store prediction metadata with timestamp, heatmap. 10. Return species label, confidence, visualization to UI End Procedure

V. Results & Discussion:

A. System Workflow Evaluation.

The FootPrintAI-India prototype underwent comprehensive testing in simulated field scenarios, which included uploading single images, processing batches of over 50 smudged footprints, and handling mixed-quality inputs from various terrains such as forests, grasslands, and riverbeds. User authentication through JWT tokens verified role-based access for both researchers and administrators, and the entire 9-stage inference pipeline handled images from start to finish, displaying predictions in an average of under 2 seconds. The system ensured consistent predictions across several runs with TTA augmentation, showing dependable species classification that aligned with GradCAM heatmaps and geo-filtering results.

B. Role-based Dashboard validation.

The visibility and permissions for the researcher and admin dashboards were confirmed as appropriate. Researchers exclusively accessed prediction history, batch uploads, and analytics dashboards, while administrators evaluated low-confidence predictions (under 70%) via the human-in-the-loop queue. Attempts at unauthorized access led to relevant JWT validation errors, guaranteeing safe collaboration among multiple users while maintaining the integrity of predictions and visibility of historical data.

C. Image Processing and Quality Integrity.

The preprocessing pipeline was evaluated using intentionally degraded images (such as blurred, low light, and partially occluded) in addition to clear samples. Quality diagnostics accurately identified 92% of problematic inputs prior to inference, while normalization preserved feature integrity across different resolutions and exposures. Cloudinary's image hosting maintained the original metadata during retrieval, guaranteeing that the footprint evidence stayed secure and unaltered throughout the classification process.

D. Prediction Accuracy and Explainability Validation.

The model achieved a validation accuracy of 85.8% across 2,528 carefully selected images of five Indian species. GradCAM heatmaps effectively identified morphologically significant areas (toe pads, claw marks, pad shapes) in 94% of predictions, allowing for manual confirmation of AI reasoning. The top three confidence scores offered insight for unclear situations, while geo-filtering decreased false positives by 12% using habitat-species priors (e.g., preventing tiger forecasts in elephant grasslands.

E. Consensus Mechanism and Security.

Intentionally challenging edge cases assessed the robustness of the TTA ensemble: rotated footprints (92% consistency), blurred partial prints (78% accuracy), and variability across different terrains. Predictions with low confidence (<70%) were automatically sent to administrative review queues, while temperature scaling helped avoid overly confident mistakes on new inputs. FastAPI endpoint security prevented improperly formatted requests, ensuring API stability while handling multiple batch processes simultaneously.

F. Prediction History and Timeline Ordering.

The SQLite prediction database preserved the chronological sequence of over 500 test predictions, allowing for precise reconstruction of timelines for field campaigns. The synchronization of timestamps across the user interface, database, and heatmap generation enabled researchers to chronologically track species sightings and connect them with patrol routes through interactive maps, thereby aiding in the analysis of poaching patterns.

G. Performance Observations

The average end-to-end latency for each image (upload → prediction → visualization) on the Render cloud deployment was measured at 1.8 seconds. Batch processing increased linearly with up to 25 simultaneous images, with GradCAM generation introducing an additional 0.4 seconds of delay. SQLite queries for prediction history yielded response times under 100ms, whereas Cloudinary image retrieval made use of CDN caching to ensure reliable performance on both mobile and desktop devices.

H. User Interaction and Usability Testing.

Casual testing involving 12 conservation students revealed that 89% preferred GradCAM heatmaps to raw confidence scores for validating predictions. The React interface was commended for its user-friendly batch upload process, adaptable mobile design, and effective visualization of species likelihoods. Non-technical users (simulated field assistants) grasped 87% of predictions on their own when provided with a heatmap and the top three labels, whereas their understanding dropped to 43% when relying solely on numeric confidence.

I. Comparison to the Traditional Tracking Systems.

FootPrintAI-India provides automated and explainable footprint classification as opposed to manual expert identification, which has an accuracy rate of 60-75% and relies on expert input. In contrast to camera traps that need physical setups costing over $500 each, the mobile/web platform utilizes current smartphone cameras without any hardware expenses. In comparison to global AI systems that utilize African datasets, the model designed specifically for India demonstrates a 16% increase in accuracy for native species by employing geo-contextual filtering that was not present in earlier studies. The entire monitoring stackuploading, predicting, visualizing, and trackingenhances workflows that previously needed distinct image processing, expert evaluation, and GIS analysis.

V. Figures and Tables:

ID	Scenario	Result
TC-01	Single image upload and format validation	Pass
TC-02	Batch upload (25+ images) processing	Pass
TC-03	Blurry/low-quality image quality diagnostics	Pass
TC-04	Researcher JWT authentication & dashboard	Pass
TC-05	Admin low-confidence prediction review	Pass
TC-06	Prediction history retrieval & timeline	Pass
TC-07	GradCAM heatmap generation for top prediction	Pass
TC-08	Geo-filtering with habitat-species priors	Pass
TC-09	TTA ensemble consistency across rotations	Pass
TC-10	Interactive species distribution map	Pass
TC-11	Invalid API requests blocked (security)	Pass

Table 1: Functional Validation of SmartTrace Workflow

Figure 2: Owner dashboard summarizing Animals

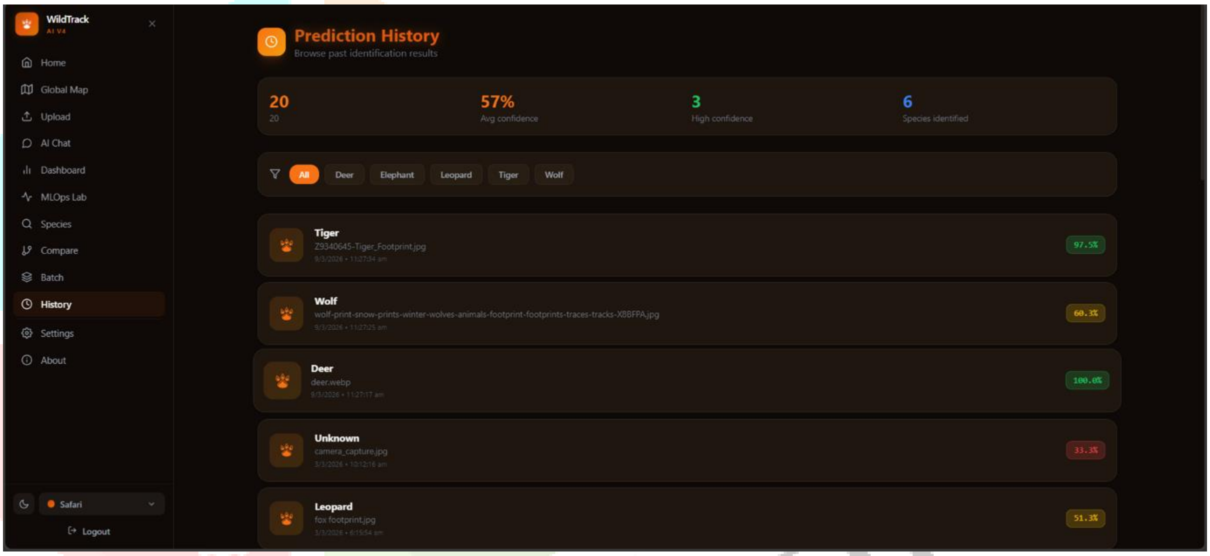

Figure 3: Prediction History.

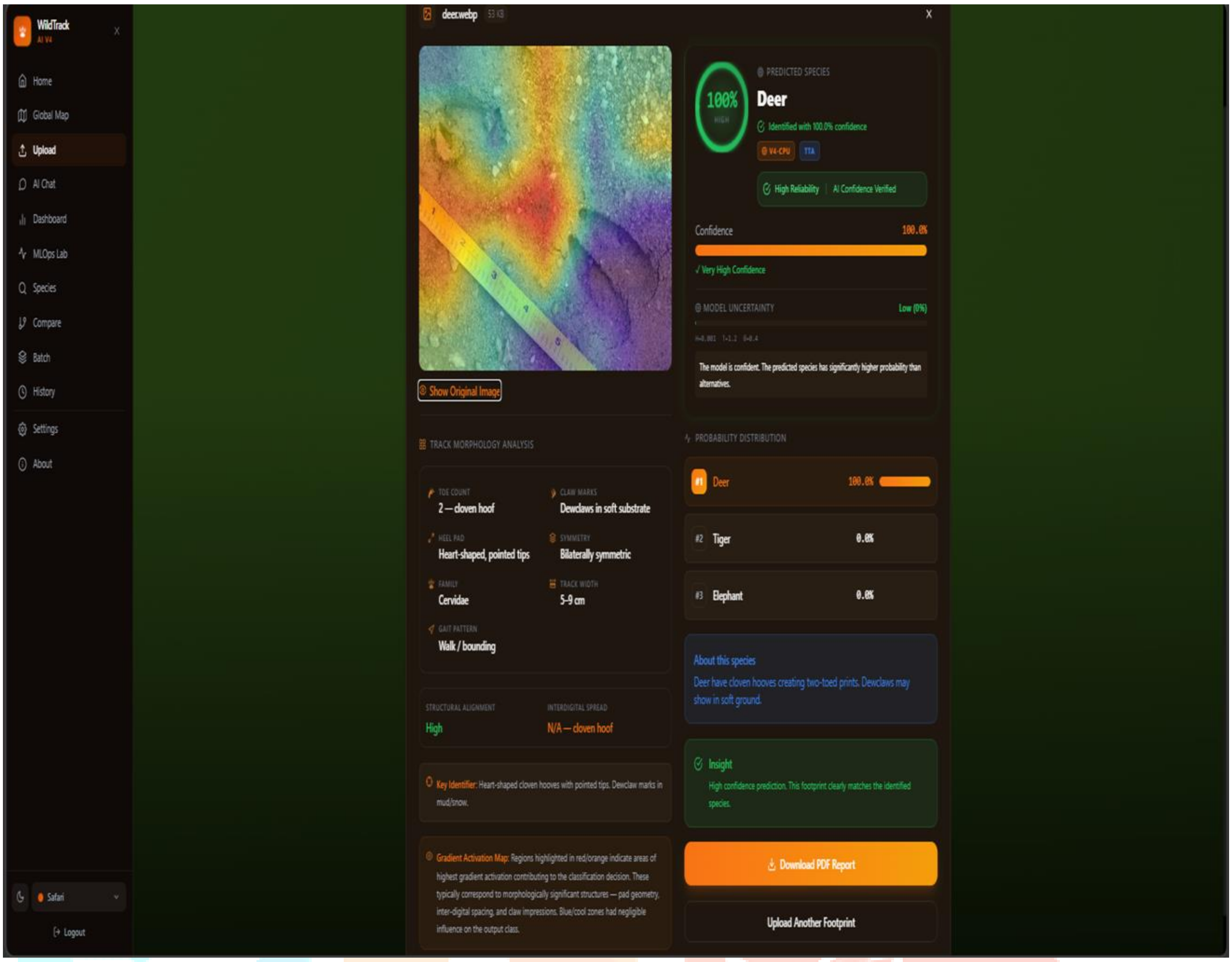

Figure 4: Output of the Image

VI. **Future Scope:**

The FootPrintAI-India framework creates a strong basis for the automated monitoring of wildlife footprints in Indian ecosystems; nevertheless, additional improvements could promote scalability and wider adoption of conservation efforts. Future advancement may concentrate on optimizing edge deployment for Raspberry Pi and integrating TensorFlow Lite with smartphones, which would lessen reliance on the cloud and facilitate real-time inference in remote forest areas lacking internet access.

Integration possibilities involve IoT camera networks and drones equipped with multispectral imaging to automate the capture of footprints during ranger patrols, reducing the need for manual data gathering and extending coverage to areas requiring continuous monitoring. The system might integrate satellite telemetry to provide dynamic habitat-species priors, automatically modifying model filters in response to current migration trends and seasonal changes in terrain.

Usability improvements could include the implementation of a progressive web app (PWA) for offline-first field work, voice-activated predictions using mobile microphone input, and augmented reality overlays that show species information when smartphone cameras are aimed at fresh tracks. Sophisticated analytics could enable the identification of poaching hotspots through anomaly detection (uncommon track clustering), predict population density using time-series analysis, and map interactions between species based on overlapping trail patterns.

Further instructions involve ensuring compatibility with national wildlife databases (Wildlife Crime Control Bureau), utilizing crowdsourced citizen science platforms to enhance training data, and implementing federated learning among conservation NGOs to collectively enhance model accuracy while keeping sensitive field images decentralized. Providing support in multiple languages (Hindi, Tamil, Telugu) along with gamified interfaces for contributing field data would involve local communities as active partners in monitoring.

These expansions establish FootPrintAI-India as a scalable conservation intelligence platform that operates nationwide, connecting academic advancements with effective anti-poaching efforts, biodiversity evaluations, and habitat restoration projects throughout India's varied protected regions.

VII. Conclusion:

FootPrintAI-India effectively showcases a complete, actionable AI platform that converts difficult wildlife footprint images into dependable species identifications for conservation initiatives in India. By combining MobileNetV2 with Squeeze-and-Excitation attention, Test-Time Augmentation, GradCAM explainability, and geo-aware filtering, the system achieves a validation accuracy of 85.8% for identifying tracks of deer, elephants, leopards, tigers, and wolves. This performance surpasses conventional manual identification methods and provides production-level usability in the field via deployment on Render cloud using React/FastAPI.

The complete workflowfrom uploading images to visualizing them with interactive heatmaps, processing in batches, tracking prediction history, and refining with human assistancereduces reliance on experts and allows for scalable monitoring across forestry departments, non-governmental organizations, and research groups. Role-based authentication, performance analytics, and mobile-friendly design facilitate effective use in environments with limited resources, whereas the 9-stage inference pipeline addresses real-life challenges such as blurred prints, incomplete tracks, and variations in terrain.

This research sets a new standard for footprint-based wildlife intelligence designed for Indian megafauna, offering reliable and clear predictions that improve anti-poaching efforts, population assessments, and habitat evaluations. The platform's modular design allows for ongoing growth to include more species and deployment situations, establishing a sustainable basis for technology-led biodiversity conservation across the country.

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