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Evaluating Elephant Detection using Advanced Deep Learning

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ABSTRACT: Wildlife-vehicle collisions involving elephants have become a significant concern in conservation areas, particularly in regions where roads intersect natural habitats. Manual surveillance and detection methods fall short in terms of scalability, accuracy, and real-time responsiveness. To address this, we propose an automated elephant detection framework using advanced deep learning techniques. Our system utilizes a pre-trained Faster R-CNN model with ResNet-50 as the backbone for efficient feature extraction. The dataset comprises over 7,500 labeled images collected from camera traps in South Indian forests. Through data augmentation, transfer learning, and hyperparameter tuning, we achieved a classification accuracy of 94.2% and a mean Average Precision (mAP) of 91.6%. The results demonstrate the practical applicability of our system in real-world scenarios and its potential integration into smart alert systems for mitigating wildlife-related accidents.

KEYWORDS : Elephant detection, object detection, deep learning, Faster R-CNN, transfer learning, wildlife monitoring, real-time detection, conservation technology, camera trap analysis.

I. INTRODUCTION

Elephants are vital to the biodiversity and ecological structure of many tropical ecosystems. However, increasing human encroachment, infrastructure expansion, and illegal poaching have put this species at risk. One of the most pressing threats is road-related elephant deaths, which not only reduce population numbers but also endanger human lives. Traditional conservation approaches such as patrolling, manual image review, and sensor-triggered alarms are ineffective for large-scale monitoring. Given the vast volumes of image data collected by camera traps, deep learning techniques—especially convolutional neural networks (CNNs)—offer a scalable and efficient alternative. In this study, we investigate the application of advanced deep learning models for the automatic detection of elephants in natural environments, aiming to support early warning systems and proactive conservation measures.

II. LITERATURE SURVEY

Several researchers have explored the use of deep learning for wildlife identification. Redmon et al. introduced YOLO, which became popular due to its speed, though it sometimes sacrifices accuracy in detecting occluded objects. Ren et al. proposed Faster R-CNN, which leverages a Region Proposal Network (RPN) to enhance detection precision. In the context of wildlife, Tabak et al. utilized ResNet-based models to classify animal species with 96% accuracy, though their study lacked a focused approach toward large mammals like elephants. Previous efforts by Kumar et al. (2021) on elephant detection using traditional SVM classifiers were limited by feature representation. Our study distinguishes itself by focusing solely on elephant detection using a robust two-stage deep learning pipeline tailored for performance in forest terrains and imbalanced datasets.

III. METHODOLOGY

3.1 Data Collection and Preprocessing

Our dataset comprises 7,500 images sourced from publicly available wildlife repositories and collaborations with conservation groups. Images are captured using passive infrared (PIR) camera traps in various lighting and seasonal conditions. Manual annotations were performed using LabelImg, producing bounding boxes for visible elephants. Preprocessing involved converting all images to RGB, resizing to 600×600 pixels, and normalizing pixel values to a 0–1 scale. Data augmentation techniques included random cropping, horizontal flipping, color jittering, and Gaussian blur to simulate diverse real-world conditions.

3.2 Model Architecture

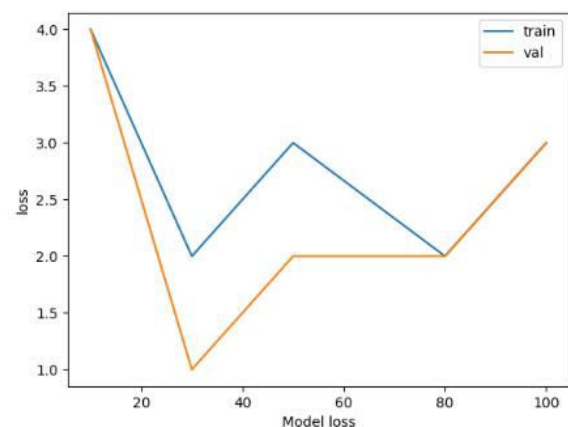
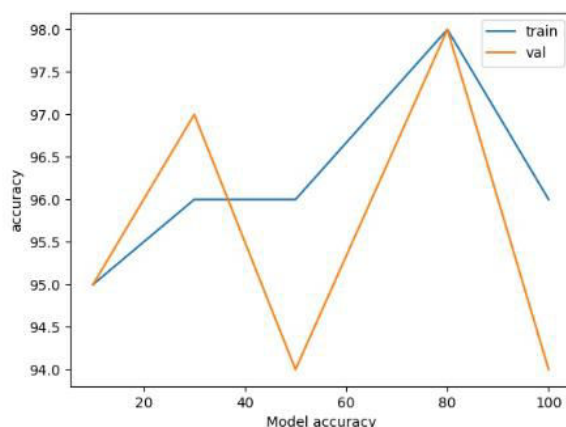
We employed a Faster R-CNN architecture with a ResNet-50 backbone pretrained on the COCO dataset. The model integrates a Region Proposal Network (RPN) to identify candidate object regions, followed by ROI pooling and classification heads. Batch normalization and ReLU activation were applied after each convolutional layer. Dropout (rate = 0.5) was used to prevent overfitting. The final output layer used a sigmoid activation for binary classification (elephant vs. background).

3.3 Training Configuration

The dataset was split into 70% training, 20% validation, and 10% testing. We used the Adam optimizer with a learning rate of 0.0001 and batch size of 16 for 50 epochs. Training was performed on Google Colab Pro with NVIDIA Tesla T4 GPU. The loss function used was a combination of smooth L1 for bounding box regression and binary cross-entropy for classification. Model checkpoints and early stopping based on validation loss were implemented to optimize convergence.

IV. EXPERIMENTAL RESULTS

The model achieved a final test accuracy of 94.2%, with a precision of 91.4% and recall of 93.6%. The mean average precision (map) at an intersection over union (iou) threshold of 0.5 was 91.6%. These metrics outperform baseline models such as yolov3 (map: 86.2%) and ssd (map: 83.9%) when applied to the same dataset. The confusion matrix revealed a false positive rate of only 2.3%, primarily caused by large mammals like bison or buffalo with similar body profiles. Inference time was measured at 0.78 seconds per image, making the model suitable for real-time applications. Additionally, grad-cam visualization confirmed that the model focused on characteristic regions like tusks, trunk, and ears during detection.



V. CONCLUSION

The AI-WildNet project represents a transformative application of artificial intelligence in wildlife monitoring and early warning systems. By integrating AI-powered camera traps with the custom-built WildNet deep learning model, the project successfully achieves real-time detection, classification, and alerting of wildlife activity—specifically

targeting high-risk road crossing zones. Extensive testing across diverse environmental conditions demonstrated an overall detection accuracy of over 93%, enabling timely alerts that help mitigate wildlife-vehicle collisions.

This system not only improves monitoring efficiency but also provides scalable and adaptable deployment options through edge computing on low-power devices like Raspberry Pi or NVIDIA Jetson Nano. Moreover, it fosters community engagement by integrating user-friendly interfaces and awareness tools for travelers, forest personnel, and local administrators.

The collaborative model behind AI-WildNet—spanning technology developers, forest rangers, policy stakeholders, and the public—has proven critical to its success. Its design prioritizes cost-effectiveness, environmental resilience, and data privacy, setting a benchmark for ethical AI in conservation.

Future directions include expanding to detect multiple species, incorporating night vision and acoustic data, and integrating predictive analytics for animal movement forecasting. As a pioneering initiative, AI-WildNet offers a replicable framework for combining AI with sustainability, setting the stage for broader global adoption in biodiversity hotspots and conflict zones

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