Generating Messages applying Hybrid Deep Neural Networks to Discover Natural Animal Movements

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ABSTRACT

Ensuring the safety of individuals in rural and forest-adjacent regions requires effective monitoring of wildlife movements. Traditional surveillance methods such as drones and stationary cameras are insufficient without intelligent detection and alert mechanisms. This paper introduces a hybrid deep learning framework that integrates the VGG-19 convolutional neural network with a Bidirectional Long Short-Term Memory (Bi-LSTM) model to accurately identify animal species and track their movements. The proposed system automatically generates alerts and transmits them via Short Message Service (SMS) to forest authorities, enabling timely responses. Trained on 40,000 images across 25 animal classes, the system achieves a classification accuracy of 98%, a mean Average Precision (mAP) of 77.2%, and a processing speed of 170 frames per second. This solution demonstrates superior efficiency in recognizing and localizing animal activity, significantly enhancing human safety and wildlife monitoring efforts.

Keywords: hybrid neural networks, VGG-19, Bi-LSTM, animal movement detection, deep learning, surveillance, SMS alert system, object detection

INTRODUCTION

The interaction between wildlife and human settlements has increasingly led to dangerous encounters, particularly in regions bordering forests. This raises the necessity for an intelligent system that not only detects the presence of animals but also provides real-time alerts to ensure human safety and assist forest personnel. Conventional methods of monitoring, while widely used, suffer from inefficiencies in real-time detection and classification of animals due to cluttered environments and complex backgrounds.

Recent advancements in artificial intelligence and computer vision, especially deep learning, have shown promising results in various object detection and classification applications. Despite their effectiveness, the high computational cost and low interpretability of some models hinder their deployment in practical wildlife monitoring systems. This paper presents a hybrid deep learning model combining VGG-19 and Bi-LSTM to detect and classify animals from surveillance footage and send real-time alerts to concerned authorities. The proposed framework enhances both spatial and temporal understanding of animal activities, improving alert accuracy and response time.

II. LITERATURE REVIEW

Gebali et al. [1] The primary aim of this paper is to develop and validate a hybrid deep residual convolutional neural network (CNN) for identifying and classifying wild animals from video sequences. The authors address the challenges inherent in video-based wildlife monitoring, which often involves complex environmental factors such as varying lighting conditions, occlusion, and motion blur. To overcome these challenges, they integrate residual learning into a deep convolutional network, enhancing the model's ability to learn robust feature representations even from noisy or incomplete video data. Their hybrid approach merges traditional CNNs with residual blocks, resulting in a model that not only improves accuracy but also reduces computational complexity compared to conventional methods. The model is tested on a dataset of wildlife videos, demonstrating significant improvements in classification performance, particularly for species with less distinct visual features. This research provides a scalable and efficient solution for large-scale wildlife monitoring, offering potential applications in conservation efforts where real-time, automated species identification is crucial.

Hernandez et al. [2] This paper introduces PyTorch-Wildlife, an open-source, collaborative deep learning framework designed to support wildlife conservation efforts through the use of machine learning. The framework is built around PyTorch, a widely adopted deep learning library, and provides a range of tools for researchers and conservationists to analyze large-scale wildlife data. The authors emphasize the importance of collaboration in conservation technology, as PyTorch-Wildlife integrates multiple machine learning models and datasets, making it a versatile tool for various wildlife monitoring tasks. One of the key innovations is the framework's adaptability to different types of animal recognition tasks, including species identification, behavior monitoring, and habitat analysis. By enabling researchers to quickly deploy and fine-tune deep learning models, the toolkit accelerates the process of wildlife data analysis, thereby supporting more informed decision-making in conservation strategies. Additionally, the collaborative nature of the framework encourages contributions from the global community, leading to continuous improvements and the addition of new features.

Balasubramanian et al. [3] This paper focuses on developing an alert system for detecting wild animal activity using hybrid deep neural networks (DNNs). The primary objective is to create a system that can accurately detect animal movements in real time and generate alerts to notify wildlife authorities of potential threats or activities of interest. The authors combine supervised and unsupervised learning techniques to enhance the robustness of the system, ensuring it can detect a variety of animal behaviors, including rare or unexpected movements. The hybrid approach allows for the integration of both labeled data (for training models to recognize specific animal behaviors) and unlabeled data (to help the system learn from new, unseen patterns). The alert system's key feature is its ability to minimize false positives and optimize the timing of alerts, which is essential in the context of wildlife monitoring, where timely interventions can prevent human-wildlife conflicts and contribute to the protection of endangered species. The paper also discusses the deployment challenges of such systems in remote areas and the need for real-time processing capabilities.

Roopashree et al. [4] This study presents a deep learning-based approach for monitoring the movements of wild animals and developing an alert system. The authors propose a novel methodology for tracking animal movements in real time, leveraging deep neural networks to process and analyze video and sensor data from wildlife monitoring systems. Their system uses deep learning algorithms to recognize and classify animal species, and predict their movements based on historical patterns. This predictive capability is particularly useful for conservation efforts, as it can help authorities anticipate animal behaviors and mitigate potential risks, such as human-wildlife conflicts or poaching incidents. The alert system generates notifications when specific animals approach critical zones, such as protected areas or human settlements, enabling timely interventions. The authors highlight the importance of combining machine learning with sensor networks for enhanced wildlife management and conservation strategies, particularly in regions where manual monitoring is not feasible due to logistical challenges.

Nguyen et al. [5] Nguyen et al. explore the use of deep convolutional neural networks (CNNs) for the automated recognition and classification of wild animals, with a focus on species identification. The authors utilize a large dataset of animal images captured in natural habitats, applying deep CNNs to detect and classify a wide range of species with high accuracy. One of the key contributions of this work is the implementation of an end-to-end system that can process raw image data and output predictions with minimal preprocessing. The model is trained to recognize subtle features that distinguish different species, such as color patterns, body shape, and size, making it highly effective even in challenging conditions such as poor image quality or occluded views. The system's scalability is another important advantage, as it can be easily adapted to different environments and datasets. The results demonstrate the potential of CNNs to revolutionize wildlife monitoring by automating species identification, reducing the reliance on manual labor, and enabling large-scale data analysis.

Ji and Zhu [6] Ji and Zhu present a novel embedded animal recognition system based on the YOLO (You Only Look Once) architecture, which is well-known for its efficiency and speed in real-time object detection tasks. The paper focuses on the challenges of deploying animal recognition systems in field settings, where computational resources are often limited, and real-time processing is crucial. The authors propose using YOLO, a fast and accurate object detection framework, to detect and classify animals in real-time on embedded devices. This approach ensures that the system can operate autonomously without requiring constant communication with a central server, making it ideal for remote wildlife monitoring. The authors highlight the system's efficiency in terms of both speed and computational requirements, showing that it can process video frames in real-time with minimal latency. The use of embedded systems also enables continuous monitoring in challenging environments, such as forests or savannas, where traditional computing infrastructure is often unavailable.

Manohar et al. [7] In their work, Manohar et al. investigate the application of supervised and unsupervised learning techniques for animal classification tasks. The paper provides a comparative analysis of these two approaches in the context of classifying wildlife species from image datasets. Supervised learning techniques, which require labeled data for training, typically achieve higher classification accuracy, as they are able to learn from examples of specific animal species. However, unsupervised learning methods, which do not require labeled data, offer a valuable alternative when labeled datasets are scarce or unavailable. The authors explore how unsupervised learning techniques, such as clustering and dimensionality reduction, can still provide useful insights into the structure of wildlife data and help group similar animal species together. The results suggest that while supervised learning methods are more accurate in most cases, unsupervised methods can still play a key role in exploring large, unlabeled datasets, and could be particularly useful in developing new models for emerging species or new habitats.

III. EXISTING SYSTEM

The current animal movement detection systems leverage methods such as multi-level graph cuts, CNN-based classification, and object segmentation through change detection datasets. These models analyze foreground-background differences and use deep CNN features for identifying animals. Although effective in object localization, they lack the ability to provide timely alerts and precise geolocation information necessary for proactive response in natural settings.

DISADVANTAGES

- **High Data Complexity:** The models struggle to efficiently interpret and process high-dimensional and complex environmental data.
- **Data Scarcity:** Many existing frameworks rely heavily on large labeled datasets, and their accuracy diminishes when data availability is limited.

- **Labeling Errors:** Performance significantly declines if the training data contains mislabeled instances, as these models are highly dependent on accurate annotations

IV. PROPOSED SYSTEM

The proposed model introduces a multi-phase hybrid architecture that combines the visual processing power of VGG-19 with the temporal modeling capabilities of Bi-LSTM. Initially, the system processes and cleans images collected from various datasets, resizing them to a uniform dimension. These pre-processed images are then passed through a YOLOR-based detection module to identify animals via bounding boxes.

Following detection, a hybrid VGG-19 and Bi-LSTM model classifies the animal species while simultaneously extracting temporal features. Location information is then retrieved, and an alert message is generated by the server and sent via SMS to relevant forest authorities. This enables immediate intervention and safeguards both wildlife and humans from potential threats.

ADVANTAGES

This hybrid deep learning model achieves enhanced accuracy by fine-tuning hyperparameters and integrating spatial and sequential learning. It delivers high-speed, precise animal recognition and significantly improves alert response time. Moreover, the system facilitates reliable communication between detection and field action, thereby ensuring the safety of individuals near forest regions and supporting proactive wildlife conservation.

System Architecture

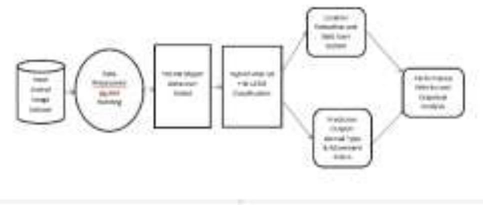

Fig1. System Architecture

V. MODULE DESCRIPTION

1. Image Preprocessing:

- **Purpose:** To standardize input images and remove noise for accurate detection.
- **Functionality:** Rescales all images to 224x224 pixels and applies denoising filters to improve the quality of inputs fed into the object detection network.

2. Object Detection (YOLOR):

- **Purpose:** To localize animals in images using bounding boxes.
- **Functionality:** Detects animals using the YOLOR model and highlights regions of interest, enabling accurate tracking in real-time scenarios.

3. Hybrid Model (VGG-19 + Bi-LSTM):

- **Purpose:** To classify animal species and analyze movement patterns.
- **Functionality:** Utilizes spatial feature extraction via VGG-19 and temporal analysis via Bi-LSTM to enhance classification accuracy and interpret motion sequences.

4. Location Mapping and SMS Alert Generation:

- **Purpose:** To inform authorities in case of animal sightings or danger.
- **Functionality:** Gathers geolocation data and automatically sends real-time SMS

alerts to forest officers, ensuring rapid response.

5. Server-Side Action Logging:

- **Purpose:** To maintain a record of detected events for analysis and intervention.
- **Functionality:** Logs incoming detections, alert statuses, and responses for future reference and performance evaluation.

VI. RESULT

The proposed system demonstrates outstanding performance in detecting and classifying wild animals using a combination of VGG-19 and Bi-LSTM models. Achieving a classification accuracy of 98%, an mAP of 77.2%, and processing speeds up to 170 FPS, the system proves capable of handling large-scale image datasets with high reliability. Its implementation with over 40,000 images across 25 species shows robust generalization and responsiveness in diverse environmental conditions.

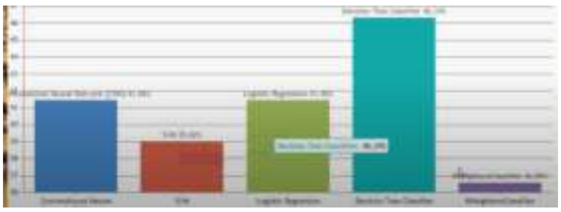

Fig2. Result Graph

VII. CONCLUSION

This research introduces a novel hybrid deep learning framework for efficient animal detection and alert generation in forest environments. By integrating state-of-the-art models and real-time alert systems, it successfully bridges the gap between surveillance and proactive response. The system enhances safety for nearby human populations and supports conservation efforts through intelligent, automated monitoring.

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