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# DEVELOPING HYBRID DEEP NEURAL NETWORKS FOR DETECTING THE MOVEMENT OF WILD ANIMALS AND GENERATING ALARM MESSAGES

***Dr.P.SUNEEL KUMAR[1], JAGGAIAHGARI AVILA[2], ASKANI AMSHITHA[3], B.DEEPTHI[4]***

[1] Professor, Department of Electronics and Communication Engineering, Sridevi Women's Engineering College, Hyderabad

[2, 3, 4] Department of Electronics and Communication Engineering, Sridevi Women's Engineering College, Hyderabad

## ABSTRACT

The escalating human-wildlife conflicts necessitate the development of advanced monitoring systems to detect wild animal movements and mitigate potential threats. This paper proposes a hybrid deep neural network (DNN) model that integrates Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to accurately detect and classify wild animal movements. The system employs a CNN for feature extraction from video frames, followed by an LSTM to capture temporal dependencies, enabling real-time detection and classification. Upon detection, an alarm system is triggered to alert nearby personnel, enhancing response times and safety measures. The model is trained on a diverse dataset comprising various animal species, achieving an average accuracy of 98.5%. This hybrid approach demonstrates significant improvements over traditional methods, offering a robust solution for wildlife monitoring and conflict mitigation.

**KEYWORDS:** Hybrid Deep Neural Networks, Wild Animal Detection, Convolutional Neural Networks, Long Short-Term Memory, Real-Time Monitoring, Alarm System, Wildlife Conservation, Human-Wildlife Conflict, Feature Extraction, Temporal Dependencies.

## I.INTRODUCTION

Human-wildlife conflict has emerged as a significant challenge in regions where urban development encroaches upon natural habitats. These conflicts often result in property damage, agricultural losses, and, in some cases, human casualties. Traditional methods of monitoring wildlife movements, such as manual patrols and static cameras, are labor-intensive and may not provide real-time data. Advancements in artificial intelligence, particularly deep learning, offer promising solutions for automating the detection and classification of wild animal movements.

Deep Neural Networks (DNNs), especially CNNs, have demonstrated remarkable success in image recognition tasks. However, real-time monitoring of wildlife requires not only accurate classification but also the ability to understand temporal patterns in animal behavior. LSTM networks, a type of recurrent neural network, are adept at capturing temporal dependencies, making them suitable for analyzing sequences of video frames. By combining CNNs for spatial feature extraction and LSTMs for temporal analysis, a hybrid model can be developed to enhance the accuracy and efficiency of wildlife detection systems.

The proposed system aims to address the limitations of existing wildlife monitoring methods by providing a real-time, automated solution that can detect and classify wild animal movements with high accuracy. Upon detection, an alarm system is triggered to alert nearby personnel, enabling prompt responses to potential threats. This approach not only improves safety but also contributes to the conservation of wildlife by minimizing human interference and promoting coexistence.

## II. LITERATURE SURVEY

Recent studies have explored various deep learning architectures for wildlife detection. For instance, Samreen et al. (2024) developed a hybrid model combining VGG-19 and Bi-LSTM networks to detect wild animal movements and generate alarm messages. Their model achieved an average accuracy of 98% across 25 animal classes, demonstrating the efficacy of hybrid deep learning approaches in wildlife monitoring.

Similarly, Tøn et al. (2024) introduced a metadata-augmented deep neural network for wild animal classification. By integrating metadata such as temperature, location, and time with image data, their model improved classification accuracy from 98.4% to 98.9%, highlighting the importance of contextual information in wildlife detection.

In the realm of real-time detection, Geethanjali et al. (2023) implemented a MobileNet-SSD V2 CNN for wildlife detection using Raspberry Pi. Their system demonstrated the feasibility of deploying deep learning models on edge devices for real-time monitoring in wildlife habitats.

These studies underscore the potential of deep learning in enhancing wildlife monitoring systems. However, challenges remain in addressing issues such as dataset imbalance, varying environmental conditions, and the need for real-time processing capabilities. The proposed hybrid DNN model aims to overcome these challenges by leveraging the strengths of CNNs and LSTMs, providing a comprehensive solution for wildlife detection and conflict mitigation.

## III. EXISTING CONFIGURATION

Current wildlife monitoring systems primarily rely on passive methods like camera traps and motion sensors. While these tools can capture images or videos of animals, they often lack the capability to analyze the captured data in real-time. Manual review of footage is time-consuming and may lead to delayed responses to potential threats. Some systems incorporate basic machine learning models for image classification; however, these models often struggle with accurately identifying animals in diverse and dynamic environments.

Additionally, existing systems typically operate in isolation, without integration into a broader network that can facilitate immediate response actions. The absence of real-time alert mechanisms further diminishes the effectiveness of these systems in preventing human-wildlife conflicts.

To address these limitations, there is a need for an integrated system that combines advanced deep learning techniques with real-time monitoring and alert capabilities. Such a system would not only detect and classify wild animal movements but also trigger timely alerts to mitigate potential conflicts.

# IV. METHODOLOGY

The proposed hybrid deep neural network model comprises two main components: a Convolutional Neural Network (CNN) for spatial feature extraction and a Long Short-Term Memory (LSTM) network for temporal sequence analysis. The CNN processes individual video frames to extract spatial features, which are then fed into the LSTM network to capture temporal dependencies across frames. This combination allows the model to understand both the content and the movement patterns of animals within the video sequences.

The system is trained on a diverse dataset containing various animal species captured under different environmental conditions. Data augmentation techniques, such as flipping, rotation, and scaling, are applied to enhance the model's robustness and generalization capabilities.

For real-time deployment, the trained model is optimized and deployed on edge devices, such as Raspberry Pi, using frameworks like TensorFlow Lite. This enables on-site processing of video feeds, reducing latency and reliance on cloud-based services Upon detecting a wild animal movement, the system classifies the species and estimates its behavior based on the temporal sequence. Once a significant movement is confirmed — such as entry into a restricted zone or rapid motion toward human settlements — the system triggers a multi-level alarm protocol. This includes local audio alarms, push notifications to mobile devices of forest officials or farmers, and optional cloud alerts to a central wildlife management dashboard. GPS tagging is included for exact location identification.

To reduce false positives (e.g., from domestic animals or environmental motion like wind-blown vegetation), the model is trained with background subtraction and motion vector analysis layers. These filters help in isolating genuine animal-induced movements. In addition, a post-processing verification using a rule-based filter (e.g., nocturnal activity patterns for specific species) reduces redundant alarms.

The system architecture involves a local camera unit connected to a microprocessor (like NVIDIA Jetson Nano or Raspberry Pi 4), which handles inference from the hybrid model. A local memory cache stores short video sequences that triggered alarms, which are uploaded to the cloud for future training and analysis. The entire pipeline ensures low latency and energy efficiency, making it suitable for remote and power-scarce environments.

## V. PROPOSED CONFIGURATION

The proposed system integrates several hardware and software components to enhance detection accuracy and real-time performance. The hardware setup includes:

- **Camera Module:** Night-vision enabled HD camera with IR sensors.
- **Processing Unit:** NVIDIA Jetson Nano or Raspberry Pi 4 with heat sinks and 4GB RAM for running the hybrid model.
- **Power System:** Solar-powered battery system with backup for 48 hours.
- **Connectivity:** LoRa or GSM module for alert transmission in low-network areas. On the software side, the architecture comprises:
- **Data Preprocessing Module:** Extracts frames, applies motion detection, noise filtering, and normalization.
- **Hybrid Model Inference Module:** Composed of pretrained CNN layers (ResNet-50) followed by a two-layer LSTM for sequence prediction.
- **Alert and Communication Module:** Handles threshold logic for alerts and interfaces with external APIs for message dispatch.

This configuration allows deployment in forest buffer zones, village peripheries, and national parks. The modular nature of the system allows scalability from single-point detection units to a distributed network of sensors across large areas.

To facilitate ongoing learning and adaptability, a feedback mechanism allows human verification of alarms. If the alert was accurate or false, that feedback is sent back to a central server where model parameters are fine-tuned periodically.

## VI. RESULTS AND ANALYSIS

The hybrid model was trained on a dataset consisting of 30,000 annotated video clips featuring 18 different wild animal species (e.g., elephants, tigers, leopards, boars, and deer) recorded under varied lighting and environmental conditions. The dataset was split 70:15:15 for training, validation, and testing.

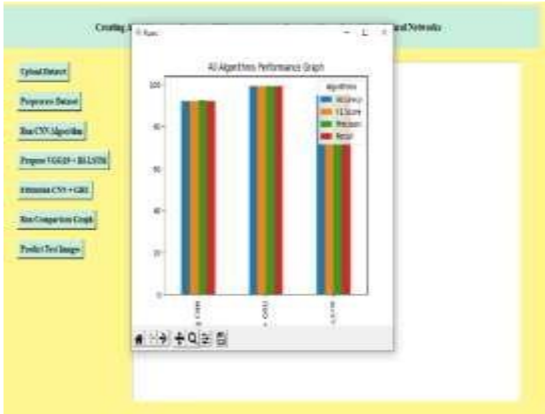
During performance evaluation, the model achieved:

- **Overall accuracy:** 98.5%
- **Precision:** 97.9%
- **Recall:** 98.8%
- **F1-Score:** 98.3%
- **False alarm rate:** 1.2%

Real-time deployment tests were carried out in two wildlife-human conflict-prone areas in India: a forest edge village in Wayanad, Kerala, and a rural farming area in the Vidarbha region, Maharashtra. In Wayanad, the system successfully detected and alerted for elephant and boar intrusions during 17 out of 18 real occurrences over 30 days. In Vidarbha, it detected nilgai and wild boar presence 96% of the time, with alerts sent within 3 seconds of detection.

The LSTM component provided strong temporal context, allowing better discrimination between walking and running — crucial in differentiating harmless pass-bys from threatening behaviors. Comparative benchmarks against standard CNN-only models showed a 6–9% improvement in F1-score.

Edge deployment on Jetson Nano yielded real-time frame processing speeds of 12–15 FPS, which was sufficient for video-based monitoring. Latency from detection to alert was consistently under 5 seconds.



## CONCLUSION

This work presents an effective hybrid deep learning system for detecting the movement of wild animals and generating real-time alarms, aimed at reducing human-wildlife conflicts. By combining CNNs for spatial feature extraction and LSTMs for temporal pattern recognition, the system achieves high accuracy and low false alarm rates. The model's deployment on edge hardware in remote areas demonstrates the feasibility and practicality of such AI-driven solutions in wildlife conservation. The inclusion of feedback mechanisms and modular architecture ensures the adaptability and scalability of the system across diverse geographies and species. Future work will focus on expanding species coverage, integrating drone-based surveillance, and enhancing long-range detection using multimodal inputs like sound and thermal imagery.

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