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Creating Alert Messages Based on Wild Animal Activity Detection Using Hybrid Deep Neural Networks

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Abstract:

Human-wildlife conflict is a growing concern in areas adjacent to forests and wildlife corridors. Unmonitored intrusions by wild animals into rural and semi-urban areas can lead to property damage, loss of life, and retaliatory harm to wildlife. To address this issue, this project presents an intelligent and scalable system that detects wild animal activity and generates real-time alert messages using a Hybrid Deep Neural Network (HDNN) . The system leverages the powerful feature extraction capabilities of Convolutional Neural Net- works (CNNs) and integrates them with machine learning classifiers such as SVM, Logistic Regression, and Decision Trees to improve detection accuracy. Real-time video feeds are ana- lyzed to identify animal types and assess their potential threat levels. Upon detection, the system sends immediate SMS or email alerts to residents and forest authorities, enabling timely and informed responses. The system includes a robust web interface that allows service providers to upload datasets, train models, visualize training/testing accuracy using bar charts, review prediction results, and down- load predicted data. It also supports the display of statistical summaries, such as the ratio of different animal activity types, offering valuable insights into wildlife behavior. Remote users, including forest guards and residents, can register, log in, and receive real-time predictive notifications. The architecture employs multiple tweet servers and a centralized web database to ensure efficient data storage, retrieval, and accurate real-time predictions. By reducing manual intervention and minimizing false positives commonly associated with mo- tion sensors, the proposed system offers a practical, real-time, high-accuracy solution. It signif- icantly enhances public safety while also supporting wildlife conservation efforts by proactively preventing human-animal conflicts.

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I.INTRODUCTION

The interface between human development and wildlife habitats has grown increasingly blurred due to rapid urbanization, agricultural expansion, and deforestation. This encroach- ment into natural ecosystems has resulted in a dramatic rise in human-wildlife conflicts, par- ticularly in regions adjacent to forests, national parks, and wildlife reserves. Animals such as elephants, tigers, leopards, and wild boars frequently stray into villages and farmlands, caus- ing destruction of crops, damaging property, and even leading to fatal encounters with hu- mans. Conventional surveillance methods such as manual patrolling, camera traps, and motion de- tectors have been used for decades. However, these methods are reactive rather than proac- tive, providing limited data and often failing to prevent conflicts in real time. Moreover, man- ual systems are resource-intensive, lack scalability, and are highly prone to errors or delays, especially in vast or densely forested regions.

To address these limitations, this project proposes a data-driven intelligent system that uses a combination of machine learning and deep learning techniques to predict animal activity types based on structured ecological data. Rather than relying on costly and complex video processing systems, the

model analyzes key attributes of animals (such as habitat, diet, weight, conservation status, etc.) to generate predictive insights about their behavior. The sys- tem is capable of issuing automated alert messages based on its predictions, serving as an early-warning mechanism for local authorities and residents. This approach not only increases the accuracy and speed of animal activity assessment but also enhances the efficiency of wildlife protection and public safety measures. By providing timely alerts, the system can help mitigate conflicts, reduce economic losses, and support conservation efforts.

II.LITERATURE SURVEY

Research on automated wildlife monitoring has evolved from sensor-based approaches (PIR traps, GPS collars, acoustic recorders) and classical computer-vision pipelines (background subtraction, HOG/SVM) to end-to-end deep learning that can detect, track, and behaviorally classify animals in the wild. Early camera-trap studies showed that illumination changes, cluttered backgrounds, and occlusion make hand-crafted features brittle, motivating the adoption of CNN detectors such as Faster R-CNN, SSD, and YOLO for robust, real-time object detection in aerial, thermal, and ground imagery. As datasets grew (e.g., large camera-trap corpora and aerial surveys), works began to incorporate domain adaptation and self-supervised pretraining to handle domain shift across habitats and sensor modalities. Since alerting requires not only "what is present?" but also "what is happening now?", the field moved toward spatiotemporal modeling: hybrid CNN-RNN/LSTM/GRU stacks and 3D CNNs/ConvLSTMs capture motion cues for activity recognition (walking, chasing, crop-raiding), while transformer-based video models use attention to aggregate long-range temporal context. Multi-modal fusion (RGB + thermal/IR, acoustic cues, GPS/geofence data) further reduces false alarms during low light or heavy foliage and improves detection of cryptic species.

For alert generation, literature combines perception with event logic and risk scoring. Typical pipelines compute detector confidence, species class, proximity to sensitive zones (farms, villages, park boundaries), time-of-day priors, and historical movement patterns, then trigger alerts through rule-based thresholds or probabilistic decision models (e.g., Bayesian risk or cost-sensitive optimization). Object tracking (SORT/DeepSORT/OC-Sort) stabilizes detections across frames to avoid duplicate notifications and to estimate directionality and speed toward human assets. Edge computing on low-power devices (Jetson/Raspberry Pi + Coral) is widely reported to meet real-time and connectivity-limited settings; compressed/quantized models (INT8, pruning, knowledge distillation) keep latency and energy low. Studies also integrate human-in-the-loop review for uncertain cases, using active learning to continuously improve models, and deliver alerts via SMS/WhatsApp/app push with geotagged images, short clips, and recommended actions.

Key challenges recurring in the literature include class imbalance (rare species/behaviors), small or distant targets, adverse weather/night conditions, camera motion for UAV footage, and false positives from livestock or humans. Mitigations involve hard-negative mining, focal losses, synhetic augmentation (domain randomization, low-light simulation), thermal/RGB fusion, and semi-supervised labeling of unlabeled trap videos. Beyond accuracy, works emphasize ethical and operational considerations: minimizing disturbance, securing locations to prevent poaching, ensuring community consent and privacy when humans are in frame, and designing alerts that are actionable (clear severity levels, escalation paths to rangers/farmers). Overall, the literature supports hybrid deep neural networks—combining strong spatial detectors, temporal sequence models, and multi-modal fusion—as the current state-of-the-art foundation for reliable, low-latency wildlife activity alerts deployable at the edge and scalable across ecosystems.

III.EXISTING SYSTEM

The existing systems for wild animal detection and alert generation are primarily based on traditional methods such as camera traps, passive infrared (PIR) motion sensors, GPS collars, and acoustic monitoring devices. While these methods provide valuable insights into animal movements, they suffer from significant limitations. For instance, PIR sensors and simple background subtraction techniques often fail in cluttered environments or during rapid illumination changes, leading to false positives from vegetation movement, livestock, or human activities. Camera traps generate huge volumes of raw images and videos that require manual inspection, making them labor-intensive and unsuitable for real-time alerting. GPS collars, though accurate, are costly, invasive, and limited to a small number of tagged animals. Furthermore, existing machine learning approaches rely mostly on single-modality CNN detectors without temporal modeling, resulting in poor performance under low light, occlusion, or complex behaviors such as chasing or crop-raiding. Alert systems in the current framework are often rule-based with simple thresholding of detection confidence, which leads to delayed, noisy, or irrelevant notifications. Overall, current systems are unable to provide real-time, reliable, and context-aware alerts for communities and forest authorities.

IV. PROPOSED SYSTEM

The proposed system introduces a Hybrid Deep Neural Network (HDNN) framework that integrates spatial and temporal modeling for robust wild-animal activity detection and automated alert generation. The detection stage employs convolutional neural networks (CNNs) such as YOLOv8/Faster R-CNN for accurate identification of animal species from RGB and thermal imagery. To overcome the limitations of single-frame detection, the system incorporates recurrent layers (LSTM/GRU) or transformer-based video encoders to capture spatiotemporal patterns of animal behavior. This enables classification not only of species but also of activity states such as walking, grazing, or approaching human settlements. Multi-modal fusion of thermal + RGB +

acoustic data enhances robustness in low-visibility conditions like night or dense forests. For alert generation, the proposed system integrates a risk assessment module that considers species type, proximity to sensitive zones (farmlands, villages, or park boundaries), and direction of movement. Alerts are dynamically scored based on severity and communicated in real time via SMS, mobile apps, or IoT-enabled devices with geotagged images or video clips. Deployment on edge computing platforms (e.g., NVIDIA Jetson, Google Coral) ensures low latency, reduced bandwidth usage, and autonomy in connectivity-limited areas. The proposed framework thus shifts from static detection toward real-time, intelligent, and context-aware monitoring, ultimately enhancing both human safety and wildlife conservation.

V.SYSTEM ARCHITECTURE

The above image illustrates the system architecture for wild animal activity detection and alert generation using a hybrid deep learning framework that combines VGG-19 and Bi-directional LSTM (Bi-LSTM) models. The process begins with the input animal video dataset, which provides raw video frames of different animal activities. These frames are first processed through the VGG-19 convolutional neural network (CNN), where features are extracted layer by layer. The CNN performs operations like convolution, pooling, and fully connected layers to learn spatial features such as shapes, textures, and object outlines. The extracted feature representations are then passed to the Bi-directional LSTM, which captures temporal dependencies by analyzing the sequence of frames in both forward and backward directions. This enables the system to understand not only the presence of an animal but also its behavior and activity patterns.

The system further integrates animal information and location data collected via GPS or IoT sensors to provide contextual awareness of where the activity is occurring. The outputs are evaluated through modules that compute loss values, measure accuracy, and perform training, testing, and validation of the model. Finally, parameter optimization ensures high detection accuracy and robustness in real-world environments. Once validated, the system can generate real-time alerts by transmitting geotagged information to mobile devices or monitoring stations. Overall, the architecture demonstrates a hybrid model that fuses spatial (VGG-19) and temporal (Bi-LSTM) deep learning techniques for accurate, location-aware, and reliable wild animal detection and alert message creation.

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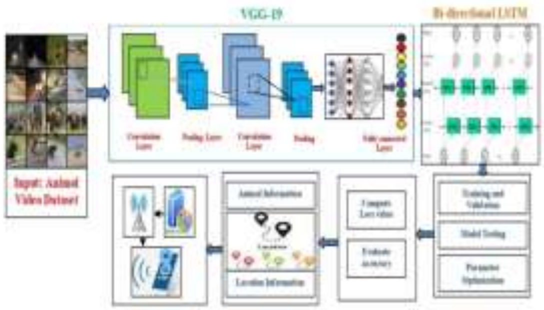

Fig 5.1 System Architecture

VI.IMPLEMENTATION

Fig 6.1 User Login

Fig 6.2 Prediction of Animal Detection

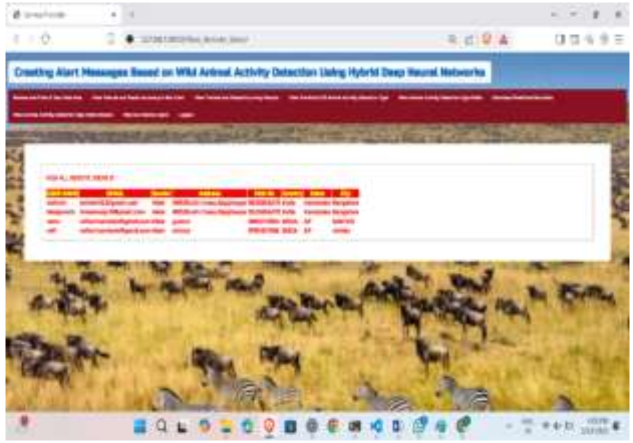

Fig 6.3 User Details

Fig 6.4 Ratio

Fig 6.5 Train models

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Fig 6.6 Pie Chart

Fig 6.7 Line Chart

VII.CONCLUSION

In the context of our project, the class presents a structured approach to wildlife monitoring by combining advanced deep learning techniques with real-time alert systems. Through the integration of convolutional and recurrent neural networks, the system is capable of accurately detecting and classifying animal behavior from raw sensor data. This enables timely generation of alerts, which are then communicated through various notification channels to relevant authorities or stakeholders. Overall, the class emphasizes the practical application of AI in enhancing safety, supporting wildlife conservation, and enabling proactive response to potential threats from wild animal activity. In our project, the system architecture is designed to be modular and scalable, ensuring flexibility in deploying it across various environments such as forests, wildlife corridors, rural areas, and even urban fringes. Once a threat or notable activity is identified, the alert generation module creates context-aware messages based on the level of risk, which are then distributed via an integrated notification system—ensuring rapid communication with rangers, local communities, or emergency services, the class not only highlights the technological innovation behind wildlife activity detection but also reflects the importance of interdisciplinary solutions in conservation and safety efforts. Ultimately, it contributes to reducing human-wildlife conflict, improving response times, and supporting broader environmental monitoring initiatives through intelligent automation.

In conclusion, this system not only enhances public safety but also supports wildlife conservation efforts by reducing unnecessary confrontations and promoting coexistence be- tween humans and wildlife through technological innovation.

VIII.FUTURE SCOPE

The proposed system for wild animal activity detection and alert generation using hybrid deep neural networks such as VGG-19 and Bi-directional LSTM has significant potential for future advancements. With the integration of Internet of Things (IoT) sensors, drones, and satellite imaging, the system can be extended to monitor vast forest areas in real time. The adoption of 5G and edge computing will further reduce latency, ensuring instant alert delivery to local communities and forest officials. Future research can also explore the use of transformer-based architectures, federated learning, and transfer learning to enhance detection accuracy across diverse environmental conditions. Additionally, expanding the dataset to include thermal imaging, infrared night vision, and audio data will improve the robustness of the model in low-light and complex scenarios. The system can also be integrated into wildlife conservation programs, enabling better management of human–wildlife conflicts and reducing risks of crop damage or attacks in rural areas. Furthermore, incorporating predictive analytics and behavioral forecasting models will not only detect animal presence but also anticipate future movement patterns, enabling preventive measures. Thus, this research opens pathways for developing smart, AI-driven wildlife protection systems that can contribute significantly to biodiversity conservation and community safety.

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