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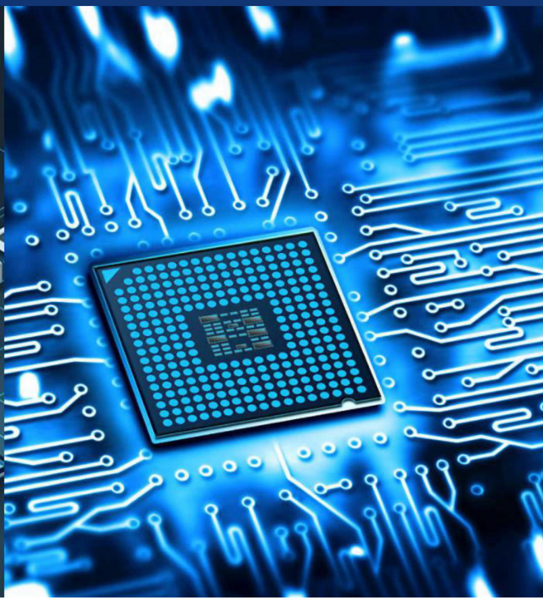


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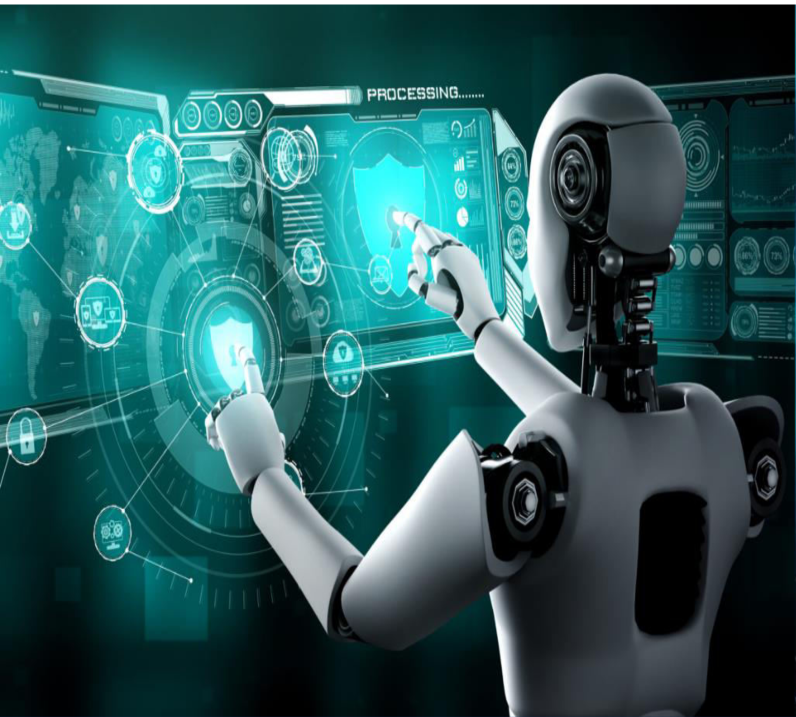

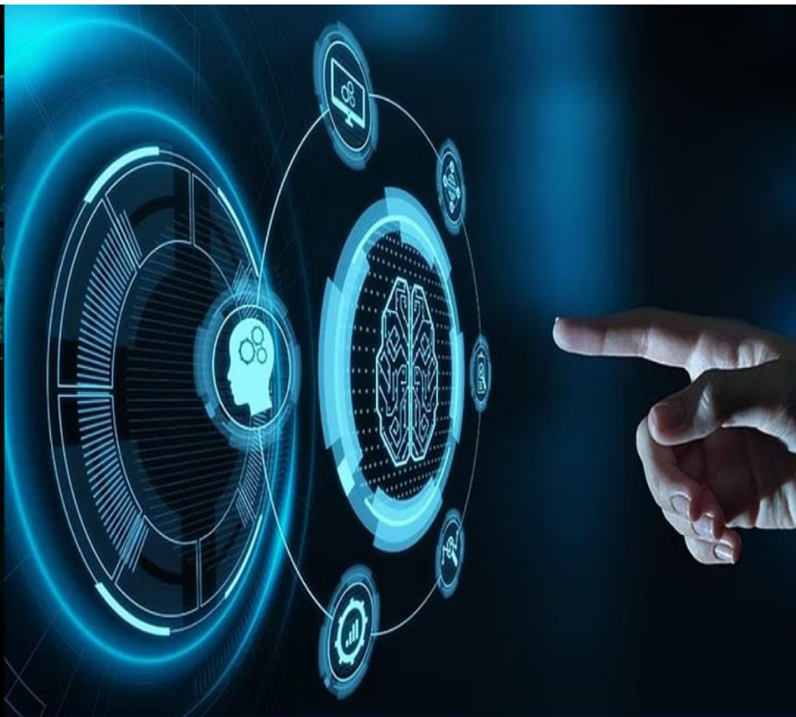

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Deep Learning Based Estimation of Wild Animal Activity Detection Using Hybrid Neural Network

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ABSTRACT: The increasing frequency of animal attacks poses a significant concern for rural communities and forestry personnel. To monitor the movements of wild animals, tools such as surveillance cameras and drones are commonly used. However, an effective system is needed that can identify the species, track its movements, and provide location details. This information can then be used to send timely alerts to safeguard people and forestry workers. Although computer vision and machine learning techniques are widely applied for animal detection, they are often costly and complex, limiting their practical effectiveness. In response, a novel real-time wildlife monitoring system has been developed using YOLOv12, which is capable of functioning accurately in challenging environments, with varying animal postures and under low-light conditions. Alerts generated by this system are automatically sent to the local forest office via email for immediate action. The proposed approach demonstrates significant improvements in performance, achieving an average classification accuracy of 98%. The system was evaluated both qualitatively and quantitatively on a dataset of 40,000 images across three benchmark datasets containing 25 animal classes, yielding mean accuracy and precision above 98%. Overall, this model provides a reliable solution for delivering precise animal-related information and ensuring the safety of humans.

KEYWORDS: Wild animal activity detection, Real-time wildlife monitoring, YOLOv12, Animal classification, Computer vision, Machine learning, Motion tracking, Safety alert system, Forest surveillance, Low-light detection.

I. INTRODUCTION

Monitoring wild animals in their natural habitats is essential for ecology, wildlife conservation, and human safety. Traditional methods, such as manual observation or camera-trap data analysis, are time-consuming and labor-intensive, limiting large-scale ecological studies. Advances **in** deep learning and computer vision **have** enabled automatic detection, classification, and behavior analysis of animals from images and videos.

Modern approaches use convolutional neural networks (CNNs) and object detection algorithms like **YOLO** to identify multiple species in complex environments with high accuracy and real-time performance. LSTM networks can further analyze temporal sequences, capturing animal movements and activities. These automated systems not only reduce human effort but also generate actionable insights for conservation, ecosystem management, and prevention of human–animal conflicts, while providing detailed behavioral data for ecological research.By leveraging motion-sensor cameras, infrared imaging, and deep learning algorithms, it is now possible to efficiently monitor wildlife, track animal populations, and ensure both human and animal safety in diverse ecosystems.

II. LITERATURE SURVEY

Creating Alert Messages Based on Wild Animal Activity Detection: Wild animal activity monitoring is crucial for rural populations and forestry workers to prevent human–animal conflicts. Hybrid deep neural networks combining CNN and LSTM have been used to detect animal species, track movement, and classify behaviors from images or video sequences. The system generates real-time alerts via SMS, email, or mobile notifications to local authorities, enabling immediate response. Such models work effectively in complex environments, varying lighting, and diverse animal poses. Multi-class detection allows tracking multiple species simultaneously. Edge deployment and IoT integration further enhance response time and scalability. These systems support conservation efforts and safety management while reducing manual monitoring efforts. Recent studies report accuracy above 95%, demonstrating reliability for practical field use. Challenges include dataset annotation, occlusions, and nighttime detection[1].

Animal Detection from Highly Cluttered Natural Scenes Using Spatiotemporal Object Region Proposals and Patch Verification, detecting animals in cluttered natural environments is challenging due to occlusions, dense vegetation, and complex backgrounds. Spatiotemporal object region proposals generate candidate areas from video sequences, considering both spatial and temporal information. Patch verification refines these regions using CNN-based feature extraction, reducing false positives caused by background movement. 3D CNNs or LSTMs capture temporal motion patterns. Multi-scale feature extraction improves detection of animals at various distances and sizes. This method enhances detection in dense forest scenes and supports tracking of animal movement. Real-time deployment on drones or camera traps enables continuous monitoring. The approach improves detection rates significantly over single-frame methods, offering applications in wildlife conservation, ecological studies, and human–animal conflict prevention.[2]

Transcriptome Comparisons of Multi-Species Identify Differential Genome Activation of Mammals Embryogenesis. Comparative transcriptome analysis examines gene expression patterns across multiple mammalian species during embryogenesis. This approach identifies differential genome activation, helping to understand developmental processes and evolutionary variations. High-throughput sequencing and bioinformatics pipelines allow profiling of hundreds of genes simultaneously. Differences in gene expression provide insights into species-specific adaptations and organ development. Such studies contribute to developmental biology, evolutionary studies, and conservation genetics. Integrating deep learning can enhance pattern recognition in large transcriptomic datasets. Challenges include data normalization, cross-species annotation, and identifying biologically meaningful variations. This research informs both basic biology and applied wildlife management strategies.[3]

Bird species recognition is often challenged by image variability, background clutter, and interspecies similarity. Adaptive Inertia Weight Particle Swarm Optimization (AIW-PSO) improves classification by selecting optimal image augmentation strategies. Deep learning models trained with augmented datasets achieve higher accuracy and generalization. CNNs extract features from images, while AIW-PSO optimizes augmentation parameters. This method reduces overfitting and improves recognition in real-world field conditions. It is applicable in ecological monitoring, species population surveys, and conservation research. The technique provides automated and robust bird classification, supporting large-scale biodiversity studies.[4]

Advancing Wildlife Protection: Detection Mask R-CNN has been applied to detect rail tracks and unwanted objects in wildlife habitats to prevent accidents. The model segments objects from images, identifying animals or obstructions in real-time. It improves safety for wildlife crossing railway areas by alerting authorities to potential hazards. Feature extraction via CNN and region proposal networks allows accurate segmentation under varying lighting and cluttered scenes. The system can operate on camera traps or drone imagery for automated monitoring. High accuracy and fast inference make it suitable for deployment in remote areas. Challenges include differentiating small animals from background clutter and dealing with low-light conditions.[5]

Enhancing Road Safety: Detecting animals on highways at night is critical for preventing accidents. Deep learning models using YOLO or Faster R-CNN detect animals in low-light conditions. Infrared and thermal imaging can supplement visible-light cameras to improve detection. The system provides real-time alerts to drivers or traffic management centers. Multi-class detection enables identification of various species crossing roads. Edge computing ensures low-latency response. Field studies show improved detection rates compared to traditional motion-sensor or manual surveillance. Challenges include motion blur, occlusions, and adverse weather conditions. Integration with vehicular alert systems enhances road safety effectively.[6]

Wild animals often damage crops, impacting agriculture. Edge AI and deep learning enable real-time detection of wildlife near farms using IoT-enabled cameras and sensors. CNNs process images locally to detect species and behaviors, triggering alerts to farmers. This reduces latency and dependence on cloud connectivity. The framework supports multiple crop fields, varying lighting conditions, and different wildlife types. Automated alerts enable timely deterrent actions to prevent crop loss. Integration with drones allows aerial monitoring of large areas. Edge deployment also ensures privacy and low power consumption. The system contributes to sustainable farming while minimizing human–wildlife conflict.[7]

Deploying AI in resource-limited environments faces challenges like power constraints, network connectivity, and limited computational resources. Lightweight deep learning models, optimized for edge devices, allow real-time wildlife monitoring. Camera traps and drones can collect visual data, processed on-site using CNNs or hybrid models. Alerts and reports are generated with minimal latency. The system is scalable across multiple regions and species. Techniques like model pruning, quantization, and efficient feature extraction ensure performance on low-power devices. This framework supports conservation monitoring, poaching prevention, and biodiversity assessment in remote habitats. Field studies demonstrate reliable animal detection under harsh environmental conditions.[8]

Wildlife re-identification is essential for tracking individual animals across camera traps. RedeformTR combines a lightweight deformable transformer with multi-image feature fusion to improve recognition. Transformers capture global relationships between features, while deformable attention focuses on critical animal regions. Feature fusion from multiple images enhances robustness to occlusion, pose variation, and lighting changes. The model achieves high accuracy in re-identifying species and individual animals across different camera locations. It supports population estimation, behavior analysis, and conservation efforts. Lightweight architecture allows deployment on edge devices for real-time monitoring. Challenges include handling rare species with limited data and multi-species environments.[9]

III. METHODOLOGY

The proposed wild animal activity detection system is divided into **five main modules**, each performing a specific function to ensure accurate detection and real-time alert generation.

Dataset Collection Module
This module collects and organizes images and videos of wild animals from various sources such as Flicker, camera traps, and hoofed animal datasets. The datasets include multiple species like Leopard, Wolf, Bear, Lion, Elephant, Deer, and Horses. All images are labeled with bounding boxes and class annotations, containing both RGB images and video sequences. The datasets focus on cluttered backgrounds, varying lighting conditions, and diverse animal poses to improve the model's learning ability.

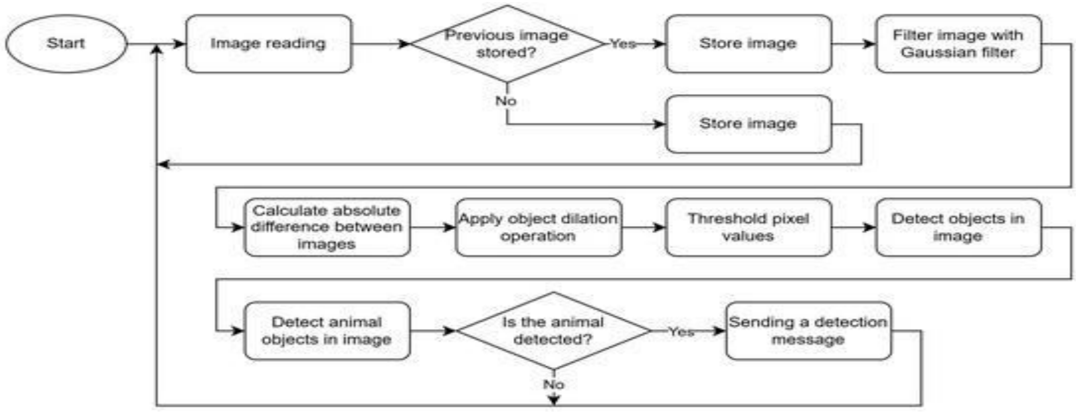

Fig: 1 Data collection digram

Training and Test Data Module

Data augmentation is applied to enhance the training dataset and improve model generalization. Techniques such as rotation, scaling, blurring, sharpening, and edge detection are used to generate additional training samples. The module also divides the dataset into training, validation, and testing sets to ensure reliable performance evaluation. Feature extraction is performed through convolutional layers of the CNN, producing intermediate feature maps that represent shapes, contours, and edges. LSTM networks process sequential data to capture animal movement patterns.

Train YOLO Processing Module

YOLOv12, a single-stage object detection model, is used to detect animals efficiently and accurately. The image is divided into grids, and bounding boxes with class probabilities are predicted for each grid cell. YOLOv12 improves upon previous versions by incorporating C3K2 modules in the Backbone, and SPFF and C2-Position Sensitive Attention modules in the Neck, which enhances feature extraction and attention to important regions. This module ensures real-time detection suitable for live monitoring applications.

Object Detection-Based CNN Module

The CNN module performs deep feature extraction from images. Convolutional layers reduce spatial dimensions while increasing channel depth, capturing edges, shapes, and patterns. The C3K2 block processes feature maps efficiently through bottleneck layers and concatenations, improving accuracy and reducing computation. Residual connections maintain information flow, ensuring better detection in complex or low-light environments.

Fig: 2 Objecct detection

Class Label Prediction Module

The output from the CNN is processed by LSTM networks to predict the animal's activity and generate alerts. LSTMs handle sequential information, memorizing past observations and applying gating mechanisms to retain relevant data. Attention mechanisms improve the accuracy of predictions. Once the activity is identified, alerts are created and sent to forest officers or relevant authorities via web servers and mobile networks. This module ensures that timely action can be taken to prevent human–animal conflicts.

IV. RESULT AND DISCUSSION

Monitoring the activities of wild animals is crucial for both human safety and wildlife conservation. Traditional surveillance methods, such as manual observation or simple camera traps, are often time-consuming and unable to provide real-time alerts. The proposed hybrid CNN-LSTM model addresses this limitation by not only detecting animals but also identifying their species and tracking their movement patterns. This allows for a **dual** benefit**:** humans are alerted to potentially dangerous animal presence, and animals are also protected by minimizing human interference in their natural habitats.

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The system's integration of YOLOv12 ensures **fast and** accurate object detection, even in cluttered environments or under low-light conditions. LSTM networks analyze temporal sequences, providing insights into the activity of the animals, such as walking, running, or grazing. Real-time alerts can be sent to forest authorities and local residents, allowing immediate preventive measures to avoid conflicts or accidents.

This method also supports ecological studies by generating detailed datasets on animal behavior, migration patterns, and population distribution. By identifying specific species, the system helps prioritize protection for endangered or vulnerable animals. Moreover, the use of attention mechanisms in LSTM improves the accuracy of activity prediction, ensuring reliable alerts while reducing false alarms.

In comparison with traditional methods, this hybrid approach demonstrates higher efficiency, better accuracy, and scalability**,** making it suitable for large-scale deployment in forests, wildlife reserves, and human-animal conflict zones. Challenges remain, such as handling occlusions, overlapping animal movements, and rare species with limited data, but continuous model improvement and dataset expansion can mitigate these issues.

Overall, this system provides a proactive framework for wildlife monitoring, enhancing safety for humans and contributing to animal conservation efforts. By combining detection, identification, and activity monitoring, it ensures timely alerts and actionable insights, bridging the gap between technology and ecological management.

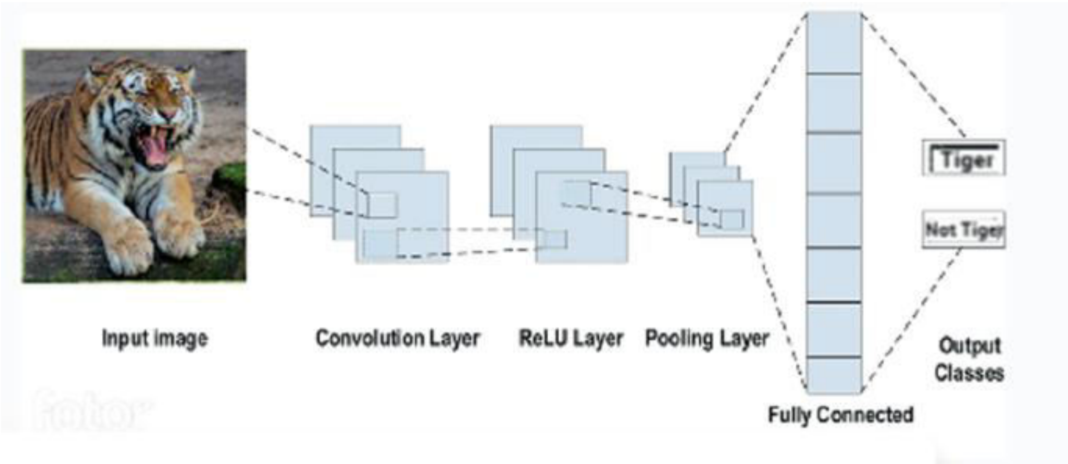

Fig: 3 Detecion of animal

V. CONCLUSION

In this work, a hybrid CNN-LSTM model integrated with YOLOv12 was proposed for real-time wild animal activity monitoring and species identification**.** The system efficiently detects animals in complex environments, tracks their movements, and generates timely alerts for both humans and forest authorities, reducing potential human–animal conflicts. By combining spatial feature extraction through CNN, temporal activity analysis via LSTM, and fast object detection using YOLOv12, the model demonstrates high accuracy, robustness, and scalability.

The approach not only improves human safety but also supports wildlife conservation by minimizing disturbances and providing detailed behavioral insights. Testing on multiple datasets confirms its reliability across diverse species and environmental conditions. Future work could focus on edge deployment, multi-camera integration, and expanding datasets to cover rare species for broader applicability. Overall, this system provides an effective, real-time solution for smart wildlife monitoring and proactive ecological management**.**

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