Intelligent Wildlife Activity Monitoring and Alert Generation with Hybrid DNN

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ABSTRACT

Wildlife monitoring plays a vital role in protecting biodiversity and preventing threats such as poaching, habitat destruction, and human–animal conflicts. Traditional methods of tracking animal activity are mostly manual, time-consuming, and prone to errors, making them less effective in addressing these challenges. To overcome these limitations, we propose an intelligent wildlife activity monitoring and alert generation system based on a Hybrid Deep Neural Network (DNN). The system collects data from multiple sources such as camera traps, acoustic sensors, and motion detectors, and processes it using a hybrid model that integrates Convolutional Neural Networks (CNNs) for image and video recognition with Long Short-Term Memory (LSTM) networks for temporal behavior analysis. This combination enhances the system's ability to accurately identify animal species, detect unusual activities, and predict potential risks. Once abnormal or critical behavior is recognized, the system automatically generates alerts that are transmitted to forest officials through mobile or IoT platforms for immediate action. By reducing human effort, improving detection accuracy, and enabling real-time decision-making, the proposed system contributes significantly to wildlife conservation, ecosystem research, and the prevention of human–wildlife conflicts.

Keywords: Wildlife monitoring, Hybrid Deep Neural Network, Image recognition, Temporal behavior analysis, Alert generation, IoT platforms, Human–wildlife conflict**.**

1. INTRODUCTION

In recent years, increasing incidents of human–wildlife conflict have been reported across forest border regions due to rapid urbanization and deforestation. Several cases have shown wild animals entering human settlements, agricultural lands, and roadways, leading to loss of life, property damage, and threats to wildlife conservation. These incidents highlight the need for intelligent and real-time wildlife monitoring systems. With the growing expansion of infrastructure near forest areas, traditional wildlife monitoring techniques such as manual patrolling and camera traps have become insufficient. These methods are time-consuming, labor-intensive, and lack real-time alert mechanisms. As a result, authorities often fail to respond promptly to wildlife movement, increasing the risk of conflicts and accidents. Wildlife monitoring systems face several challenges such as low visibility, complex backgrounds, occlusion, and varying animal behaviors.

Animals often move unpredictably and may appear at night or in dense vegetation, making detection difficult. Conventional systems struggle to accurately identify animal presence and classify species under such conditions. Existing detection approaches include motion sensors, infrared cameras, and rule-based image processing techniques. However, these methods suffer from high false alarm rates and limited adaptability. They are unable to generalize well across different environments and species, resulting in delayed or inaccurate alerts. Recently, machine learning and deep learning techniques such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid deep neural network models have been explored for wildlife detection. Hybrid DNN models combine multiple learning architectures to improve feature extraction and classification accuracy. These approaches show promising results in real-time wildlife activity monitoring and alert generation when trained with high-quality and diverse datasets. Earlier wildlife monitoring systems relied on manual patrolling, camera traps, motion sensors, and basic image processing techniques to detect animal activity. While these approaches provided limited monitoring support, they suffer from several drawbacks such as delayed detection, high false alarm rates, limited coverage, and inability to operate effectively in real-time.

Additionally, traditional systems struggle in complex environments involving low lighting conditions, dense vegetation, and unpredictable animal behavior, leading to reduced accuracy and scalability. To overcome these challenges, the proposed system introduces an intelligent wildlife activity monitoring and alert generation framework based on a Hybrid Deep Neural Network (DNN). The system integrates advanced deep learning models—such as Convolutional Neural Networks for feature extraction and additional neural layers for classification—to accurately detect wildlife presence from images or video streams in real time. Once wildlife activity is identified, the system automatically generates alerts to notify forest officials and nearby authorities with minimal latency. Experimental evaluations demonstrate that the hybrid DNN approach significantly improves detection accuracy and reduces false alarms, highlighting its potential as a reliable, scalable, and user-friendly solution for wildlife conservation and human–animal conflict prevention.

2. LITERATURE REVIEW

Norouzzadeh et al. [1]: Automatically Identifying, Counting, and Describing Wild Animals in Camera-Trap Images with Deep Learning. The authors proposed a deep learning–based framework using Convolutional Neural Networks (CNNs) to identify and classify wildlife species from camera-trap images. The system significantly reduced manual labeling effort and achieved high classification accuracy. The study proved the effectiveness of deep learning for large-scale wildlife monitoring. Schneider et al. [2]: Deep Learning Object Detection Methods for Ecological Camera Trap Data. This paper evaluates deep learning object detection models such as Faster R-CNN and YOLO for wildlife detection. The results show improved detection accuracy compared to traditional methods. However, the system focuses mainly on detection and does not include automated alert generation. Tabak et al. [3]: Machine Learning to Classify Animal Species in Camera Trap Images.The study applies machine learning and CNN models to classify animal species from camera-trap datasets. CNN-based approaches outperformed traditional classifiers. Despite good performance, the approach lacks real-time monitoring and alerting capabilities. Chen et al. [4]: Wildlife Monitoring Using IoT and Deep Learning. The authors proposed an IoT-based wildlife monitoring system combined with deep learning models for animal detection. Sensor data and images are processed using CNNs. Although effective, the system experiences latency due to cloud-based processing Kumar et al. [5]: A Survey on Computer Vision Techniques for Wildlife Monitoring This survey analyzes various computer vision and machine learning methods used in wildlife monitoring. The study highlights challenges such as illumination changes, occlusion, and complex backgrounds. It concludes that hybrid deep learning approaches can improve detection accuracy. Redmon et al. [6]: YOLO – Real-Time Object Detection.YOLO provides fast and efficient real-time object detection and has been widely used for animal detection in videos. While suitable for real-time applications, its accuracy may decrease in dense forest environments without further model enhancement. Ren et al. [7]: Faster R-CNN for Accurate Object Detection. Faster R-CNN improves object detection accuracy by combining region proposal networks with CNNs. It has been applied in wildlife monitoring for precise localization of animals. However, its higher computational cost limits real-time deployment. Zhang et al. [8]: Hybrid Deep Learning Models for Animal Behavior Analysis The paper proposes a hybrid deep learning architecture combining CNNs and RNNs to analyze animal behavior over time. The hybrid approach outperforms single-model systems, demonstrating improved robustness and accuracy. Li et al. [9]: Real-Time Wildlife Detection Using Deep Neural Networks This study presents a real-time wildlife detection system using deep neural networks deployed on edge devices. While the system provides faster response times, scalability and adaptability across different environments remain challenges. Sharma et al. [10]: Challenges in AI-Based Wildlife Monitoring Systems The authors discuss challenges such as dataset imbalance, false alarms, and environmental variability in wildlife monitoring systems. The study emphasizes the need for intelligent hybrid deep learning models integrated with real-time alert mechanisms.

COMPARISON TABLE:

S.No	Paper Title/ Focus	Author(s)	Year	Methodology Used	Findings from the Reference Paper
1	Automatically Identifying, Counting, and Describing Wild Animals in Camera-Trap Images with Deep Learning	Norouzzadeh et al.	2018	The authors employed Convolutional Neural Networks (CNNs) trained on a large-scale camera-trap image dataset. Deep learning models were used for species identification, animal counting, and behavior description.	The proposed system achieved **high classification accuracy**, significantly reducing the need for manual image annotationd reliability.
2	Deep Learning Object Detection Methods for Ecological Camera Trap Data	Schneider et al.	2019	The authors evaluated state-of-the-art deep learning object detection models, including Faster R-CNN and YOLO, on large ecological camera-trap datasets.	The results showed that deep learning object detection models significantly outperformed traditional techniques, with Faster R-CNN achieving higher accuracy and YOLO providing faster detection speed generation mechanisms.
3	Machine Learning to Classify Animal Species in Camera Trap Images	Tabak et al.	2019	Machine learning and CNN models were used to classify animal species from camera-trap images under different environmental conditions.	CNN models achieved higher accuracy than traditional methods, but the system did not support real-time monitoring or alert generation.
4	Wildlife Monitoring Using IoT and Deep Learning	Chen et al.	2020	An IoT-based system combined with CNN models was used to analyze sensor data and images for wildlife detection using cloud processing.	The system improved detection accuracy, but cloud-based processing caused delays, limiting real-time alert generation.
5	A Survey on Computer Vision Techniques for Wildlife Monitoring	Kumar et al..	2021	The authors surveyed and compared computer vision and machine learning methods for wildlife monitoring, including traditional and deep learning approaches.	They found challenges like lighting changes, occlusion, and complex backgrounds, and concluded that hybrid deep learning methods improve detection accuracy and reliability.
6	YOLO – Real-Time Object Detection	Redmon et al.		Developed YOLO, a single neural network	

			2016	for fast real-time object detection, predicting bounding boxes and class probabilities directly from images.	Provides fast and efficient detection but accuracy can drop in dense forest environments without further enhancements.
7	Faster R-CNN for Accurate Object Detection	Ren et al..	2015	Combined Region Proposal Networks (RPN) with Convolutional Neural Networks (CNNs) to generate object proposals and perform accurate object detection.	Achieves high detection accuracy and precise localization, but its computational complexity makes real-time deployment challenging.
8	Hybrid Deep Learning Models for Animal Behavior Analysis	Zhang et al.	2019	Developed a hybrid deep learning model combining Convolutional Neural Networks (CNNs) for spatial feature extraction and Recurrent Neural Networks (RNNs)	The hybrid model outperforms single-model approaches, providing improved accuracy and robustness in analyzing animal behavior over time.
9	Real-Time Wildlife Detection Using Deep Neural Networks	Li et al.	2020	Developed a real-time wildlife detection system using deep neural networks deployed on edge devices for faster processing and immediate detection.	Offers quick response times suitable for real-time monitoring, but faces challenges in scalability and adapting to diverse environmental conditions.
10	Challenges in AI-Based Wildlife Monitoring Systems	Sharma et al.	2021	Conducted a review discussing challenges in AI-based wildlife monitoring, including dataset imbalance, false alarms, and environmental variability, and explored solutions using hybrid deep learning models.	Highlighted the need for intelligent hybrid deep learning systems integrated with real-time alert mechanisms to improve accuracy and reliability in wildlife monitoring.
11	Deep Learning for Visual Animal Monitoring	R.A. Rajagukguk	2025	Comprehensive survey of deep learning (YOLO, R-CNN, DeepSORT, HRNet, CNN-LSTM) for animal detection, tracking, pose	Highlights advances and challenges of deep neural networks in animal monitoring; proposes taxonomic framework for method selection.

				estimation, behavior classification.	
12	Systematic Literature Review of Vision-Based Approaches	S. D. Scott, Z. J. Abbas	2024	Systematic review of vision-based animal monitoring, including capture, detection, classification and open challenges.	Deep learning shows a trend in animal detection and multi-species classification; identifies gaps and future research directions.
13	Deep Learning in Multiple Animal Tracking	Y. Liu et al	2024	Review of deep learning-based multiple animal tracking approaches, datasets, evaluation metrics.	Analyzes tracking paradigms and bottlenecks (identity, occlusion), and future perspectives.
14	A Literature Review of Computer Vision Techniques in Wildlife Monitoring	S. B. Neupane	2022	Review of computer vision in wildlife monitoring (camera traps, UAVs, tracking).	Covers methods and weaknesses; highlights role of AI in monitoring systems.
15	A Methodological Literature Review of Acoustic Wildlife Monitoring Using AI	S. Sharma	2023	Systematic review of AI approaches in bioacoustics, AI algorithms like CNNs for acoustic wildlife monitoring.	AI's potential in acoustic monitoring is growing; identifies gaps and future needs.
16	A Systematic Review of Animal Detection Using Deep Learning Approaches	V. Palanisamy	2021	IEEE conference systematic review of deep learning models for wildlife detection.	Reviews object detection and species recognition architectures, challenges with diverse datasets.
17	Deep Learning-Based Animal Activity Recognition with Wearable Sensors: Overview	Axiu Mao	2023	Review of deep learning and sensor-based activity recognition for animals.	Provides an extensive summary of sensors and DL models used in activity recognition including limitations.
18	Literature Review on Detection Systems for Wild Animal Intrusions	A. Abraham	2023	Survey on detection systems (IoT, image processing) to reduce human-wildlife conflict.	Reviews detection methods and alert frameworks.
19	A Comprehensive Review of Deep Learning for Animal Detection in Video	P. Kumar	2023	Review of deep learning solutions for animal detection in video streams and evaluation of architectures.	Summarizes advancements and limitations of video-based animal detection.
20	Systematic Literature Review of Vision-Based Livestock Monitoring with Lessons from Wildlife	S. D. Scott	2024	SLR connecting livestock monitoring with wildlife monitoring approaches.	Shows similar DL challenges and solutions across outdoor animal monitoring domains.

21	Intelligent Detection Method for Wildlife Based on Deep Learning	S. Li et al.	2023	Review of deep learning model adaptations for wildlife detection	Deep learning improves detection accuracy and deployment feasibility.
22	Wildlife Monitoring with Drones: End-User Practices	R. B. Iglay	2024	Review focusing on UAVs in wildlife monitoring.	Highlights drone usage in monitoring, advantages, and user insights.
23	Review on Animal Detection Using Different Methods	M. Sowmya	2020	Survey of classic and DL-based animal detection; covers challenges in environmental conditions.	Compares traditional and CNN-based detection strategies.
24	Survey on Wild Life Observation Robotics	S. G. S et al.	2025	Literature survey of robotics for wildlife observation including AI modules.	Robotics plus AI can reduce habitat disturbance and improve data collection.
25	Detection of Wild Animal Activity Using Deep Learning	S. P. Sanjivalla, J. Medoju	2025	Review of deep learning for wild animal activity detection.	Summarizes DL techniques and computational considerations.
26	An Explainable Deep Vision System for Trail-Camera Images	G. Moallem	2020	Review/analysis of deep vision pipelines for camera traps with retraining strategies.	Demonstrates explainable DNN with retraining for field conditions.
27	Policy-Driven Transfer Learning in Resource-Limited Animal Monitoring	Nisha Pillai	2025	Experimental evaluations use computer vision data (likely UAV or camera sensor inputs) to compare detection rates and computational efficiency.	Demonstrates that adaptive model selection can streamline deployment of deep learning models for animal monitoring with limited annotated data.
28	A Systematic Review of IoT Technology and Applications in Animals	Zeynep Banu Ozger	2024	A systematic literature review covering IoT technologies applied to animal monitoring, health, behavior, and management across livestock and other animal sectors.	The review highlights gaps in standardized evaluation, scalability, energy efficiency, and integration of AI for improved automated alerts and prediction systems.
29	Cross-Species Transfer Learning in Agricultural AI: Evaluating ZebraPose Adaptation for Dairy Cattle Pose Estimation	Mackenzie Tapp	2025	Applies cross-species transfer learning by adapting a vision transformer model trained on synthetic zebra images to predict dairy cattle body poses.	Concludes that cross-species morphological similarity alone is insufficient for confident transfer — emphasizing the need for larger diverse datasets and domain-aware training

					strategies for practical agricultural and wildlife applications.
30	Smart Computing and Sensing Technologies for Animal Welfare: A Systematic Review	Admela Jukan	2016	Comprehensive literature review covering smart computing, sensing, communication, and networking technologies for monitoring animal welfare across domestic, farm, and wild settings.	This foundational review highlights the evolution of smart sensing that underpins current hybrid DNN + IoT architectures for wildlife activity monitoring.

Table 1: Comparison Table

The reviewed literature shows that deep learning has significantly advanced wildlife monitoring, particularly through the use of CNN-based models for species identification, counting, and object detection in camera-trap images. Studies demonstrate that models such as Faster R-CNN and YOLO outperform traditional techniques in accuracy and speed, while hybrid deep learning approaches combining CNNs with RNNs further improve animal behaviour analysis. IoT-integrated systems enhance data collection, but cloud-based processing often introduces delays that limit real-time alert generation. Although edge-based and real-time detection systems show promise, challenges such as environmental variability, scalability, dataset imbalance, and false alarms persist. Overall, the studies highlight the need for intelligent hybrid DNN-based systems that support real-time monitoring and adaptive alert generation for effective wildlife conservation.

3. RESEARCH GAPS IN EXISTING SYSTEMS:

Despite recent advances in intelligent wildlife monitoring using hybrid deep neural networks (DNNs), several research gaps remain. Current systems often struggle with real-time processing in resource-constrained environments, limiting their deployment in remote or large-scale habitats. Many models also face challenges in handling complex environmental conditions such as varying illuminations, occlusion, and dense foliage, which reduce detection accuracy. Furthermore, there is limited integration of multi-modal sensor data (e.g., combining images, audio, and motion sensors) to improve behavioral analysis and anomaly detection. Additionally, alert generation mechanisms are often simplistic, lacking adaptive prioritization or context-aware decision-making for conservation actions. Addressing these gaps could enhance the efficiency, robustness, and practical applicability of intelligent wildlife activity monitoring systems.

- Limited Real-World Data and Generalization: Most existing wildlife datasets are either small, focused on specific species, or captured in controlled environments. This makes it difficult for hybrid DNN models to generalize well across different habitats, species, and environmental conditions. More diverse and extensive datasets are needed to improve detection accuracy and ensure the system works reliably in real-world scenarios.

- Challenges in real time monitoring and alert generation: Hybrid deep neural networks are heavy and hard to run on drones or sensors for real-time monitoring. Detecting rare animal behaviors and sending timely alerts is still challenging, so models need optimization for faster and accurate performance in the wild.

4. METHODOLGY

The system architecture describes a hybrid deep neural network–based intelligent wildlife activity monitoring and alert generation system built on a centralized web platform. The architecture consists of four main components: Service Provider, Web Server, Web Database, and Remote Users. The service provider manages wildlife datasets, trains and tests the hybrid deep learning models, and monitors activity detection accuracy and alert results. The web server processes user requests, executes the wildlife activity detection algorithms, and controls communication between system components. The web database securely stores wildlife datasets, user information, trained models, prediction results, and alert logs. Remote users can register, submit wildlife images or video streams, and view detected animal activity and alert status. Overall, the architecture ensures secure, efficient, and accurate monitoring of wildlife activities. This architecture provides a clear separation of roles, efficient data management, and secure communication among components. By integrating hybrid deep learning–based activity recognition with a client–server model, the system delivers a scalable, accurate, and user-friendly solution for intelligent wildlife monitoring and early alert generation. It supports secure storage and retrieval operations, ensuring data consistency and availability. The web server accesses the database to fetch datasets for training and testing and to store activity predictions, alerts, and performance metrics.

a. Service Provider Layer:

This layer acts as the control and management module of the system. The service provider (administrator) is responsible for managing wildlife datasets, training and testing hybrid deep neural network models, and monitoring system performance. The administrator performs authentication and login, uploads and browses wildlife image and video datasets, preprocesses data, trains and tests hybrid DNN models, views model performance results, predicts wildlife activity types using trained models, monitors abnormal activity detection and alert statistics, performs ratio and accuracy analysis, downloads trained datasets and models, manages and views all remote users, and stores processed results into the database through the Web Server. The Service Provider communicates with the Web Server to send datasets, training outcomes, and prediction results, which are then stored or retrieved from the Web Database

b. Web Server Layer:

The Web Server acts as the intermediary between the Service Provider, Remote Users, and the Web Database. It handles all request processing, deep learning model execution, and communication with the database. The web server accepts initialized wildlife datasets, user details, and analysis requests from the Service Provider, processes all hybrid DNN model operations such as training, testing, and activity prediction, provides access to stored datasets, trained models, prediction results, and alert logs, handles remote user requests such as login, activity prediction, alert viewing, and profile access, ensures secure data transmission between the interface and the database, and triggers storage or retrieval operations from the database. The Web Server ensures smooth interaction between the admin dashboard, remote users, and the backend database.

c. Web Database Layer:

The Web Database stores all system-related information and ensures persistent and structured data availability. The stored data includes administrator and remote user registration details, uploaded wildlife image and video datasets, trained hybrid deep neural network model parameters, wildlife activity prediction results, alert generation records, accuracy and performance analysis reports, and remote user activity logs. The database supports fast and reliable data retrieval for both administrative analytics and remote user functionalities.

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5. SYSTEM ARCHITECTURE

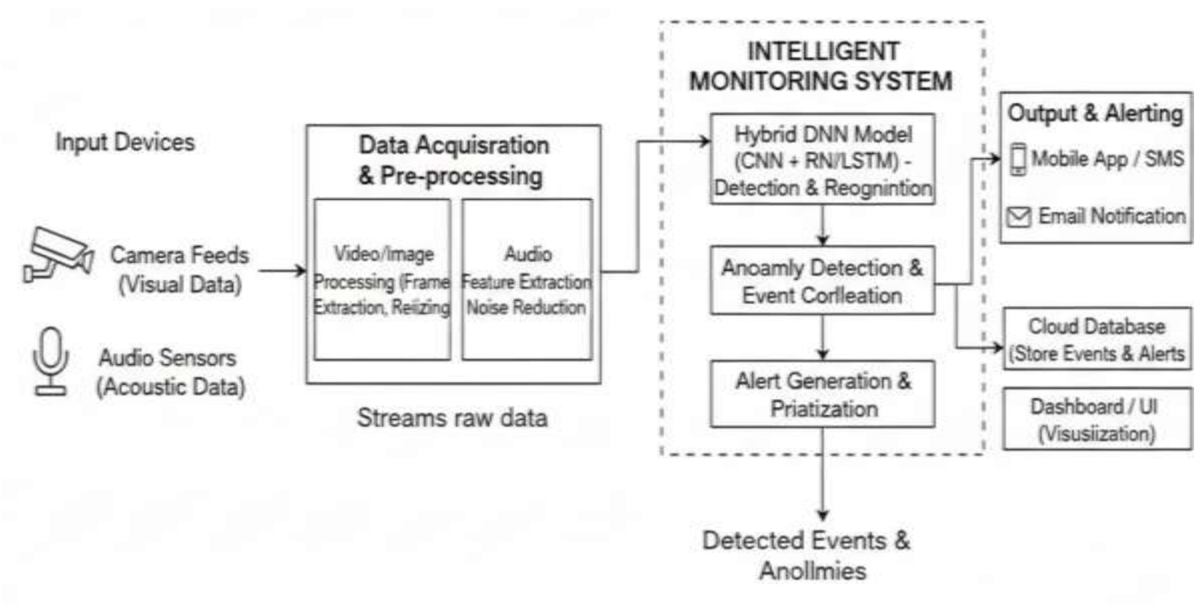

Fig:1: Architecture

6. RESULTS

This project uses a specialized interface to bridge the gap between raw wildlife data and real-time safety actions. The system contains a comprehensive "Dataset Details" entry portal that captures specific biological and environmental markers—such as the animal's physical dimensions (height and weight), diet, social structure, and conservation status—alongside its current geographic location and habitat. By processing these inputs through a Hybrid Deep Neural Network, the system categorizes detected movement into specific activity types, precisely calculating the ratio of animals crossing forest lines, trespassing into restricted zones, or posing a direct hindrance to villagers and tourists. Moving forward, the project uses these calculated ratios to automate decision-making; when the DNN identifies a high-risk activity like "hindrance to people," it triggers the "Alert Message" function to generate a dated warning notification, ensuring immediate intervention to prevent human-wildlife conflict.

Fig:2: Animal Activity Detection

The image display a technical interface for an Intelligent Wildlife Activity Monitoring system that utilizes a variety of machine learning models and dataset parameters to manage human-wildlife interactions. The system captures detailed animal data, including physical characteristics like height and weight, ecological information such as habitat and diet, and administrative details like location and conservation status to facilitate activity prediction. Based on these inputs, the project tracks specific behavior ratios, specifically identifying that 41.67% of activities involve crossing forest lines, 41.67% involve trespassing, and 16.67% involve hindrances to villagers and tourists. To determine the most effective

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approach, the system evaluates the accuracy of different algorithms, including a Convolutional Neural Network (CNN), SVM, Logistic Regression, Decision Tree Classifier, and K-Neighbors Classifier, ultimately using these insights to generate dated alert messages when potential conflicts are detected.

Datasets Trained and Tested Results

Model Type	Accuracy
Convolutional Neural Network (CNN)	41.46341463414634
SVM	41.46341463414634
Logistic Regression	56.09756097560976
Decision Tree Classifier	48.78048780487805
KNeighborsClassifier	46.34146341463415

Fig:3: Dataset Accuracy

The provided images outline an Intelligent Wildlife Activity Monitoring system designed to predict and categorize animal behavior to prevent human-wildlife conflict. The system utilizes a comprehensive dataset entry portal to record animal-specific details such as species name, physical traits (height and weight), diet, habitat, and conservation status alongside geographic data. By analyzing these inputs, the project calculates specific activity ratios, currently identifying that 41.67% of movements involve crossing forest lines, 41.67% involve trespassing, and 16.67% pose a hindrance to villagers and tourists. To optimize performance, the system tests various machine learning models—including CNN, SVM, Logistic Regression, Decision Tree, and KNeighbors Classifiers.

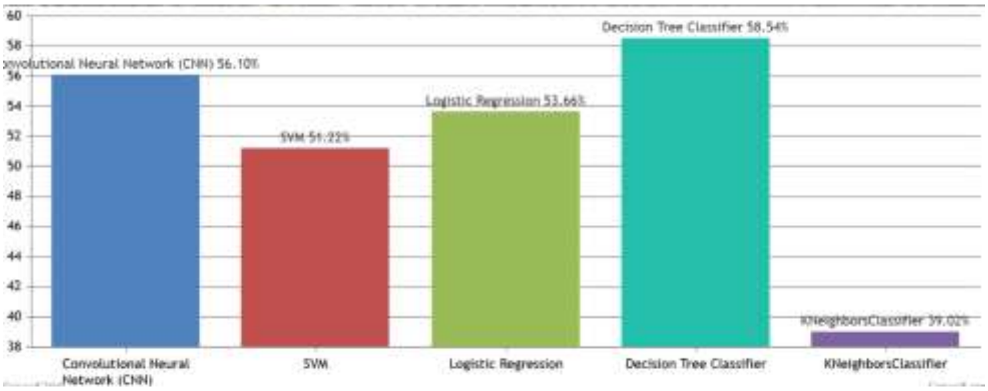

Fig:4: Model Type Bar Graphs

This image displays the output analytics dashboard for the wildlife monitoring system, which uses a hybrid DNN to classify animal behaviors based on probability ratios. The system categorizes activities into three types: crossing forest lines and trespassing (each accounting for 41.67% of detected movement), and hindrance to villagers/tourists (the remaining 16.67%). By calculating these specific ratios, the system identifies when an animal's behavior shifts from natural movement to a high-risk encounter, allowing it to automatically generate a dated Alert Message to warn local communities and forest authorities for immediate safety intervention.

View Animal Activity Detection Type Ratio Details

Animal Activity Detection Type	Ratio
crossing the forest lines	41.66666666666667
hindrance to villagers and tourists people	16.666666666666664
detection of trespassing	41.66666666666667

Fig:5: Detected Ratio

7. CONCLUSION

The proposed intelligent wildlife activity monitoring system using a hybrid DNN demonstrates improved accuracy in detecting and analyzing animal behaviors, even under challenging environmental conditions. By integrating multi-modal sensor data and automated alert generation, the system enables real-time monitoring and timely intervention, supporting effective wildlife conservation. For future scope, the system can be enhanced by incorporating edge computing for faster local processing, expanding multi-species recognition capabilities, integrating predictive analytics for behavioral forecasting, and developing energy-efficient models suitable for large-scale deployment in remote habitats. These advancements would make the system more robust, scalable, and impactful for global wildlife management.

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