



# AI-BASED WILD ANIMAL DETECTION AND WARNING SYSTEM USING HYBRID DEEP LEARNING MODELS

<sup>1</sup> SUBINAYA MAHOPATRA, <sup>2</sup> P.V ANIL KUMAR, <sup>3</sup> DIRICHINTA D NAGENDRA, <sup>4</sup> MALAPATI NARENDRA REDDY, <sup>5</sup> DUDEKULA PEDDA KASIM, <sup>6</sup> PARSAPU RAVINDRA KUMAR

<sup>1</sup> ASST., PROFESSOR, DEPARTMENT OF CSE (AI) & AIML, KRISHNA CHAITANYA INSTITUTE OF TECHNOLOGY AND SCIENCES,DEVARAJUGATTU, PEDDARAVEEDU (MD), MARKAPUR.

<sup>2</sup> ASSOC., PROFESSOR, DEPARTMENT OF CSE (AI) & AIML, KRISHNA CHAITANYA INSTITUTE OF TECHNOLOGY AND SCIENCES,DEVARAJUGATTU, PEDDARAVEEDU(MD), MARKAPUR.

<sup>3,4,5,6</sup> STUDENT, DEPARTMENT OF CSE (AI) & AIML, KRISHNA CHAITANYA INSTITUTE OF TECHNOLOGY AND SCIENCES,DEVARAJUGATTU, PEDDARAVEEDU (MD), MARKAPUR.

## ABSTRACT

Wild animal activity detection and alert generation play a crucial role in preventing human–wildlife conflicts and ensuring environmental safety in forest and rural regions. This study proposes a hybrid deep neural network-based approach for accurately detecting wild animal movements from surveillance data such as images, videos, and sensor inputs. The system integrates convolutional neural networks (CNN) for spatial feature extraction and recurrent neural networks (RNN) or long short-term memory (LSTM) networks for temporal pattern analysis of animal movement behavior. By combining these models, the system effectively identifies the presence, type, and activity level of wild animals in real time. Once a potential threat is detected, automated alert messages are generated and sent to forest authorities or nearby residents through communication channels such as SMS or mobile notifications. Experimental results demonstrate improved detection accuracy and reduced false alarms compared to traditional methods. The proposed system enhances wildlife monitoring efficiency and supports timely decision-making for disaster prevention and public safety.

**Keywords:** Wild animal detection, deep learning, hybrid neural networks, CNN, LSTM, alert system, wildlife monitoring, human–wildlife conflict, real-time detection, image processing.

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## I. INTRODUCTION

Human–wildlife conflict has become a growing concern due to increasing deforestation, urban expansion near forest



regions, and the movement of wild animals into human settlements. Incidents involving wild animal attacks not only pose threats to human life and property but also endanger animal safety. Therefore, efficient monitoring and early warning systems are essential to minimize such conflicts and ensure timely intervention.

With advancements in computer vision and deep learning, automated wildlife detection systems have gained significant attention. Traditional monitoring methods, such as manual surveillance and sensor-based alarms, are often unreliable, time-consuming, and limited in coverage. These systems also fail to provide real-time analysis and intelligent decision-making capabilities.

Deep learning techniques, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have shown remarkable success in image and video analysis tasks. CNNs are highly effective in extracting spatial features from images, while RNNs and LSTM networks are capable of analyzing temporal patterns in sequential data, such as animal movement behavior over time.

The integration of these techniques in a hybrid deep neural network model enables accurate detection of wild animal activity from surveillance feeds. When a potential threat is identified, the system generates automated alert messages and notifies concerned

authorities or nearby communities. This proactive approach enhances wildlife monitoring, improves response time, and helps in preventing dangerous encounters between humans and wild animals.

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## II. LITERATURE REVIEW

Several research studies have been conducted in the field of wildlife monitoring and animal activity detection using computer vision, sensor networks, and deep learning techniques. Early approaches primarily relied on motion detection and sensor-based systems, which used infrared sensors and camera traps to detect animal presence. However, these methods often produced false alarms due to environmental noise and lacked intelligent classification capabilities.

Wang et al. [1] proposed a traditional image processing-based wildlife detection system using background subtraction and motion tracking techniques. Although effective in controlled environments, the system struggled with complex forest conditions and varying lighting scenarios.

Liu et al. [2] introduced a machine learning-based approach for animal classification using handcrafted features such as texture and shape descriptors. While this improved classification accuracy, the method required extensive feature engineering and was not robust for real-time applications.



With the advancement of deep learning, CNN-based models have been widely adopted for wildlife image classification. Norouzzadeh et al. [3] demonstrated the use of deep CNNs for automated identification of wild animals from camera trap images, achieving high accuracy in species recognition. Similarly, Tabak et al. [4] applied deep learning models to large-scale wildlife datasets, showing improved performance over traditional methods.

Further improvements were made by integrating temporal analysis models such as LSTM networks. Chen et al. [5] combined CNN and LSTM architectures to analyze video sequences for animal movement detection, enabling better understanding of behavioral patterns over time.

Recent studies by Mathuram et al. [6] and Schneider et al. [7] have explored hybrid deep learning frameworks that combine spatial and temporal feature extraction for real-time wildlife monitoring systems. These approaches have significantly improved detection accuracy and reduced false positives.

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### III. EXISTING SYSTEM

The existing systems for wild animal activity detection and monitoring are mainly based on

traditional surveillance methods such as camera traps, infrared sensors, motion detectors, and manual observation by forest officials. These systems are widely used in forest regions to track animal movement and prevent human-wildlife conflicts.

Camera trap systems capture images or videos when motion is detected; however, they often generate large amounts of irrelevant data due to environmental factors like moving branches, rain, or lighting changes. This leads to high false alarm rates and requires significant manual effort for data analysis.

Sensor-based systems such as infrared and ultrasonic sensors are used to detect animal presence. While they are useful for basic detection, they lack the ability to classify animal types or analyze complex movement patterns. These systems also have limited range and cannot provide intelligent decision-making.

Some existing approaches use basic image processing and machine learning techniques for animal recognition. However, these methods depend heavily on handcrafted features and are not effective in real-time scenarios with varying environmental conditions.

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### IV. PROPOSED SYSTEM



The proposed system introduces a hybrid deep neural network-based framework for real-time wild animal activity detection and automated alert generation. The system is designed to overcome the limitations of traditional surveillance and sensor-based methods by using advanced deep learning techniques for accurate and intelligent wildlife monitoring.

The architecture of the proposed system integrates Convolutional Neural Networks (CNN) for extracting spatial features from images and video frames, and Recurrent Neural Networks (RNN) or Long Short-Term Memory (LSTM) networks for analyzing temporal patterns of animal movement. This hybrid model enables the system to detect not only the presence of wild animals but also their behavioral activities over time.

The input to the system is obtained from surveillance cameras, camera traps, or video feeds installed in forest and sensitive areas. The data is preprocessed by resizing, noise removal, and frame extraction before being passed to the deep learning model. The CNN component identifies and classifies animal species, while the LSTM component tracks movement sequences to understand activity patterns.

Once a potential threat or unusual animal activity is detected, the system automatically generates alert messages. These alerts are sent to forest authorities, rescue teams, or nearby

residents through SMS, email, or mobile notifications to ensure quick response and safety measures.

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## V. METHODOLOGY

The methodology of the proposed hybrid deep neural network-based wild animal activity detection system consists of several well-defined stages: data collection, preprocessing, feature extraction, model training, detection, and alert generation.

Initially, data is collected from surveillance cameras, camera traps, and publicly available wildlife datasets containing images and videos of different wild animal species. These datasets include various environmental conditions such as day, night, forest regions, and low-light scenarios to ensure model robustness.

In the preprocessing stage, raw input data is cleaned and prepared for analysis. For images and videos, steps such as resizing, frame extraction, noise reduction, normalization, and augmentation are applied. This helps improve model performance and generalization.

Next, feature extraction is performed using a hybrid deep learning approach. A Convolutional Neural Network (CNN) is used to extract spatial features such as shape, texture, and appearance of animals from images. For video sequences, a Recurrent

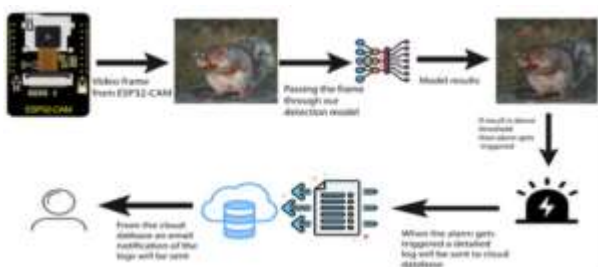
Neural Network (RNN) or Long Short-Term Memory (LSTM) network is used to capture temporal dependencies and movement patterns of animals over time.

The extracted features are then passed to the classification layer, where the model identifies the type of animal and determines whether the detected activity is normal or potentially dangerous. The system is trained using labeled datasets and optimized using techniques such as backpropagation and gradient descent.

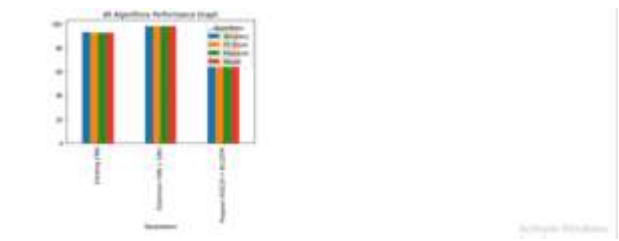
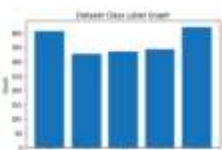
Once the model detects suspicious or high-risk animal activity, the alert generation module is activated. Automated alerts are sent through SMS, email, or mobile notifications to forest officials and nearby residents.

## VI. SYSTEM MODEL

### System Architecture



## VII. RESULTS AND DISCUSSIONS





## VIII. CONCLUSION

The proposed hybrid deep neural network-based system for wild animal activity detection provides an efficient and intelligent solution for monitoring wildlife and preventing human-animal conflicts. By integrating Convolutional Neural Networks (CNN) for spatial feature extraction and

Recurrent Neural Networks (RNN) or LSTM for temporal analysis, the system achieves accurate detection and classification of wild animal activities in real time.

Compared to traditional surveillance and sensor-based methods, the proposed approach significantly reduces false alarms and improves detection accuracy under varying environmental conditions. The automated alert generation feature ensures timely notifications to forest authorities and nearby communities, enabling quick response and preventive actions.

Overall, the system enhances wildlife monitoring capabilities by combining advanced deep learning techniques with real-time alert mechanisms. It contributes to improved safety, better wildlife management, and effective reduction of human-wildlife conflicts, making it a reliable and scalable solution for environmental protection applications.

## IX. FUTURE WORK:

The future enhancements of the wild animal activity detection system can focus on improving accuracy, scalability, and real-time performance. One major improvement is the integration of advanced deep learning architectures such as Transformer-based vision models and YOLO (You Only Look Once) for



faster and more accurate real-time object detection in complex forest environments.

Future work can also include the use of edge computing and IoT devices to process data directly at surveillance points, reducing latency and improving response time for alert generation. Integration with drone-based monitoring systems can further enhance coverage in large and inaccessible forest areas.

Another important enhancement is the incorporation of multi-sensor data fusion, combining video feeds with thermal imaging, audio signals, and motion sensors to improve detection reliability in low-visibility conditions such as night or dense forest regions.

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