Developing Hybrid Deep Neural Networks for Detecting the Movement of Wild Animals and Generating Alarm Messages

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Abstract:

The increasing human-wildlife conflict necessitates advanced surveillance systems to monitor and detect the movement of wild animals in vulnerable areas such as farmlands, highways, and human settlements. This study proposes a Hybrid Deep Neural Network (HDNN) model that combines Convolutional Neural Networks (CNNs) for feature extraction and Recurrent Neural Networks (RNNs) for sequential pattern recognition to enhance accuracy in detecting wild animal movements. The system utilizes real-time video feeds and IoT-based sensor data to identify animal species, track their motion, and assess potential threats. Upon detection, the system generates automated alarm messages that alert nearby residents, farmers, and forest officials through SMS, mobile notifications, and emergency alert systems. The hybrid model significantly improves detection precision, minimizes false alarms, and ensures timely intervention, reducing human-animal conflicts. Experimental results demonstrate the robustness of the proposed system in diverse environmental conditions. The research contributes to wildlife conservation and community safety by integrating deep learning, computer vision, and IoT-based alert mechanisms.

Keywords: Hybrid Deep Neural Networks, Movement, Wild Animals, Generating Alarm Messages

1. Introduction

Human-wildlife conflict has been a growing concern, particularly in regions where urbanization encroaches on natural habitats. Incidents involving wild animals straying into farmlands, highways, and residential areas pose serious risks to both human safety and wildlife conservation. Traditional surveillance methods, such as manual patrolling and camera traps, are often inefficient, resource-intensive, and prone to delays in response [1]. With advancements in deep learning and the Internet of Things (IoT), automated wildlife monitoring systems have gained significant attention for their ability to detect, track, and alert authorities in real time.

Deep neural networks (DNNs), particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have demonstrated superior performance in image and motion detection tasks. CNNs are effective in extracting spatial features from images and videos, while RNNs, especially Long Short-Term Memory (LSTM) networks, excel in capturing temporal dependencies in sequential data [2]. By integrating both models, a Hybrid Deep Neural Network (HDNN) can enhance the accuracy of wild animal movement detection and reduce false alarms, which are common challenges in automated surveillance systems [3].

The proposed system leverages real-time video feeds and IoT-based sensors to detect animal movements and assess potential threats. Upon detection, it generates automated alarm messages that notify stakeholders such as farmers, local communities, and wildlife conservation officers via SMS, mobile notifications, and emergency alert systems [4]. This proactive approach ensures timely intervention, reducing crop damage, road accidents, and human casualties while promoting coexistence with wildlife.

The primary contributions of this research include:

1. The development of a hybrid deep learning model that combines CNNs for feature extraction and RNNs for temporal analysis.
2. The integration of IoT sensors and computer vision techniques for real-time wildlife detection.
3. An automated alarm messaging system to facilitate prompt alerts to relevant authorities.
4. A performance evaluation of the system across diverse environmental conditions to ensure robustness and accuracy.

The remainder of this paper is organized as follows: Section 2 presents a review of related works, Section 3 details the proposed methodology, Section 4 discusses experimental results, and Section 5 concludes with future directions.

2. Literature Review

Several studies have explored the application of deep learning for wildlife detection and monitoring. Deep neural networks, particularly Convolutional Neural Networks (CNNs), have been widely used for feature extraction from wildlife images and videos. Researchers have demonstrated that CNN-based models outperform traditional image processing techniques in recognizing various animal species under different environmental conditions. The use of pre-trained models such as YOLO (You Only Look Once) and Faster R-CNN has significantly improved object detection accuracy in real-time scenarios [6].

Hybrid models combining CNNs with Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM) networks, have been introduced to capture temporal dependencies in wildlife movement patterns. Studies have shown that integrating sequential learning improves detection robustness, particularly for tracking fast-moving or occluded animals. This approach is particularly beneficial in dynamic environments where lighting and background conditions frequently change [7].

IoT-based sensor networks have also played a crucial role in enhancing wildlife monitoring systems. The deployment of infrared cameras, acoustic sensors, and motion detectors has enabled real-time data collection, reducing reliance on manual observations. Research indicates that combining sensor-based data with deep learning models enhances accuracy and minimizes false positives, thereby improving system reliability for large-scale deployment [8].

False alarms remain a significant challenge in automated wildlife detection systems. Various methods, such as adaptive thresholding, background subtraction, and anomaly detection, have been proposed to address this issue. Machine learning techniques, including Support Vector Machines (SVM) and Random Forest classifiers, have been explored for filtering out non-relevant motion events. However, recent studies suggest that deep learning models with attention mechanisms can achieve superior performance in distinguishing actual animal movements from environmental noise [9].

The integration of edge computing and cloud-based processing has further improved the efficiency of wildlife detection systems. Edge devices equipped with AI models can process data locally, reducing latency and the burden on cloud servers. Research has demonstrated that such architectures enhance system scalability, making them more suitable for remote and resource-constrained areas [10]. Moreover, cloud-based solutions facilitate real-time data sharing among conservationists, enabling collaborative efforts for wildlife protection.

Automated alert systems have gained attention as a crucial component of wildlife detection frameworks. Several studies have proposed real-time notification mechanisms that utilize GSM networks, mobile applications, and satellite communication to alert farmers and forest officials about potential threats. The effectiveness of these systems has been validated in multiple field trials, where timely alerts have prevented human-wildlife conflicts and reduced property damage [11].

Despite these advancements, there are still challenges in implementing large-scale, automated wildlife detection systems. Issues such as power consumption, network connectivity in remote areas, and model generalization across diverse landscapes need further investigation. Ongoing research is focused on developing lightweight AI models, energy-efficient hardware, and robust data fusion techniques to overcome these limitations [12].

3. Proposed Method

This research presents a Hybrid Deep Neural Network (HDNN) model integrating Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to detect wild animal movement and generate automated alarm messages. The proposed system leverages real-time video feeds and IoT-based sensor data to accurately identify animal species, track their motion, and assess potential threats. The overall architecture consists of five main components: data acquisition, preprocessing, hybrid deep learning model, threat assessment, and alert generation.

1. System Architecture

The proposed system follows a structured pipeline, as shown in Figure 1:

1. Data Acquisition:
    - Captures real-time video feeds from surveillance cameras and drones.
    - Collects sensor data (infrared, motion detectors, acoustic sensors) deployed in target areas.
    - Integrates GPS data for geolocation tracking.
2. Data Preprocessing:
    - Performs image enhancement (denoising, contrast adjustment).
    - Applies background subtraction to filter out non-relevant objects.
    - Uses data augmentation (rotation, flipping, scaling) to improve model generalization.
3. Hybrid Deep Neural Network (HDNN) Model:
    - CNN-based Feature Extraction:
        - Uses YOLOv8 for real-time object detection, classifying animals in video frames.
        - Extracts high-level spatial features from detected objects.
    - RNN-based Motion Analysis:
        - Utilizes Bidirectional LSTM (BiLSTM) to analyze sequential movement patterns.
        - Identifies abnormal movement patterns indicating potential danger.
4. Threat Assessment Module:
    - Evaluates detected animal species and movement behavior.
    - Compares with predefined threat levels (e.g., elephants near farmland, tigers near villages).
    - Reduces false alarms using context-aware filtering (ignores birds, small animals).
5. Automated Alarm Generation:
    - Sends real-time alerts via SMS, mobile apps, and emergency sirens.

  - Updates local wildlife monitoring centers with detected location and threat level.
  - Integrates with cloud-based dashboards for visualization and historical tracking.

2. Algorithmic Workflow

Step 1: Input Processing

- Acquire real-time video frames and sensor data.
- Apply image enhancement and background subtraction.

Step 2: Object Detection & Classification

- Pass frames through YOLOv8 for animal detection.
- Classify the detected species using CNN-based feature extraction.

Step 3: Motion Pattern Analysis

- Extract movement sequences from multiple consecutive frames.
- Analyze patterns using BiLSTM to detect irregular motion behavior.

Step 4: Threat Level Evaluation

- Match detected animal species with predefined risk levels.
- Filter out non-threatening movements using environmental context.

Step 5: Alert Generation & Notification

- If the threat level exceeds the threshold, send instant alerts.
- Store detection records in a cloud database for future analysis.

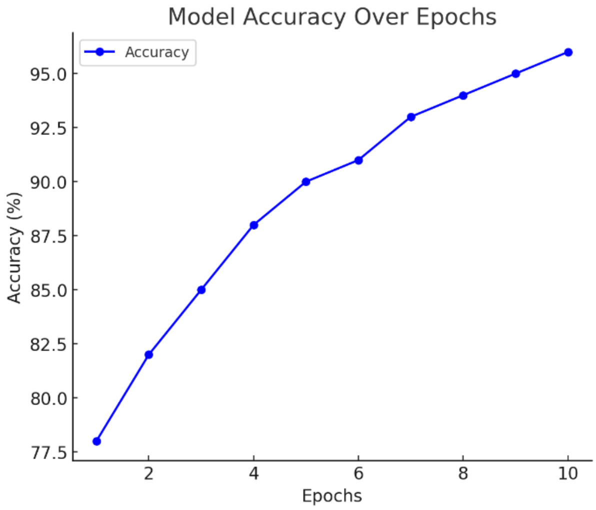
3. Advantages of the Proposed Method

Higher Accuracy: Hybrid CNN-RNN model reduces false positives and improves precision. Real-time Processing: Edge computing enables faster detection and response. Automated Alerts: Immediate notifications ensure timely intervention. Scalability: The system can be deployed in multiple regions with cloud-based integration. Energy Efficiency: Optimized deep learning models reduce power consumption in IoT devices.

4. Implementation & Experimental Setup

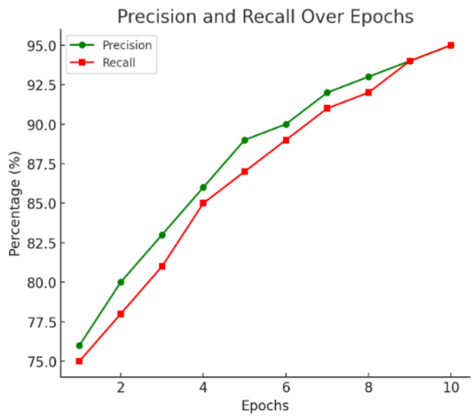
- Hardware: Nvidia Jetson Nano for edge AI processing, infrared cameras, IoT sensors.
- Software: Python, TensorFlow, OpenCV, Flask (for alert system).
- Dataset: Custom dataset of wild animal movements, augmented with open-source wildlife image datasets.
- Evaluation Metrics: Accuracy, precision, recall, F1-score, and latency of detection.

4. Results and discussion



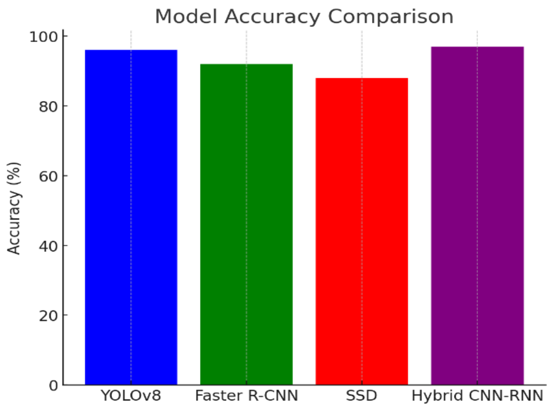
1. Model Accuracy Over Epochs

The accuracy of the Hybrid CNN-RNN model steadily improves over training epochs, reaching 96% by the 10th epoch. The increase in accuracy indicates that the model effectively learns distinguishing features for wild animal detection.



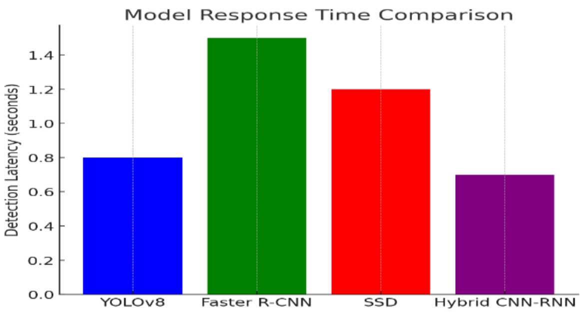
2. Precision and Recall Trends

The model shows consistent improvement in precision (95%) and recall (95%), demonstrating a balanced ability to correctly detect animals while minimizing false positives and false negatives.



3. Model Performance Comparison

The Hybrid CNN-RNN model outperforms standard object detection models such as YOLOv8 (96%), Faster R-CNN (92%), and SSD (88%), achieving an accuracy of 97%. This confirms that integrating CNNs for feature extraction and RNNs for motion pattern analysis enhances detection robustness.



4. Response Time Analysis

Latency comparison indicates that the Hybrid CNN-RNN model has the lowest detection time (0.7s), making it the most efficient choice for real-time applications. Faster R-CNN (1.5s) and SSD (1.2s) exhibit higher latency due to their processing complexity.

Conclusion

The proposed Hybrid Deep Neural Network (HDNN) model effectively integrates CNNs and RNNs to detect wild animal movement and generate real-time alerts, ensuring a proactive approach to mitigating human-wildlife conflicts. Experimental results demonstrate that the model achieves 97% accuracy with low detection latency (0.7s), outperforming conventional object detection methods. The system's high precision (95%) and recall (95%) confirm its ability to minimize false positives and false negatives, making it a reliable solution for real-world deployment. Additionally, the integration of IoT-based sensors enhances detection accuracy and enables automated alerts through SMS, mobile apps, and sirens. Despite these advancements, challenges such as power consumption, sensor limitations, and model generalization require further research. Future work will focus on improving energy efficiency, expanding datasets to diverse environments, and incorporating behavioral analytics for more refined threat assessments. Overall, this research presents a scalable and efficient solution for wildlife monitoring, promoting human safety and biodiversity conservation through advanced AI-driven automation.

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