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# Creating Alert Messages based on Wild Animal Detection

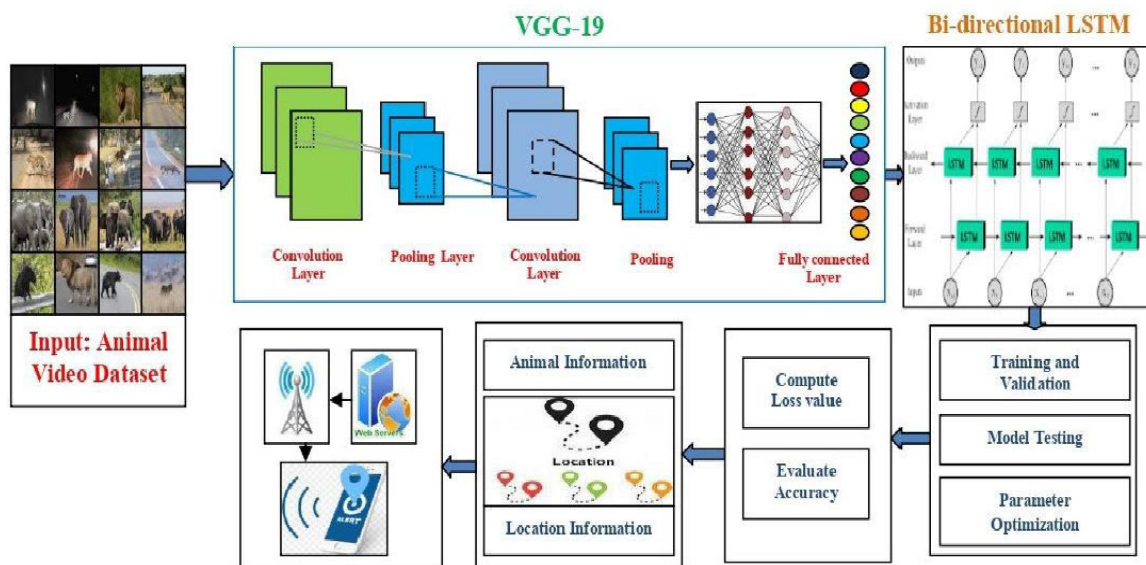
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**ABSTRACT:** This project introduces an innovative system for automated wild animal activity detection using hybrid deep neural networks. The system processes visual data (images/videos) captured in natural habitats to identify and classify various animal species. A hybrid deep learning architecture is employed to enhance detection accuracy and efficiency. Upon detection, the system generates real-time alerts, enabling timely responses for wildlife monitoring, conservation efforts, and mitigation of human-wildlife conflict. The developed system has the potential to contribute significantly to ecological research, anti-poaching initiatives, and the preservation of biodiversity. The real-time alert system supports proactive interventions, reducing risks to both humans and wildlife.

**KEYWORDS:** Animal detection ,VGG-Net, Bi-LSTM, convolutional neural network, activity recognition, video surveillance, wild animal monitoring, alert system.



## I. INTRODUCTION

Wild animal detection systems play a critical role in addressing human-wildlife conflicts and promoting safety and conservation. These systems employ cutting-edge technologies like machine learning and IoT to identify and track animal movements efficiently. By using advanced models such as CNN (VGG-19) and Bi-LSTM, they provide precise spatial and temporal analysis, enabling real-time detection and classification. Inputs can range from images and videos to live feeds, making them adaptable to diverse environments and scenarios. Integration with alert systems, such as

Twilio, ensures timely notifications to stakeholders, facilitating proactive responses to animal presence. The modular and scalable architecture of these systems allows deployment in areas like agricultural lands, forests, and urban borders. Challenges like environmental constraints and dataset limitations are acknowledged, with continuous improvements addressing these issues. Ethical considerations, including minimal disruption to wildlife, are prioritized for sustainable deployment. These systems not only reduce manual monitoring workloads but also contribute valuable insights to ecological research. As technological advancements continue, wild animal detection systems offer immense potential to revolutionize wildlife monitoring and conflict prevention.

## II. LITERATURE REVIEW

The study by R. Sato, H. Saito, Y. Tomioka, and Y. Kohira focuses on energy reduction methods for wild animal detection devices, particularly for edge devices operating in remote areas without access to commercial power. The authors propose four innovative techniques to optimize energy consumption: motion sensor sensitivity adjustment, which reduces unnecessary image captures; attachment of a hat, which minimizes sensor activations; motion detection using a frame difference method, which decreases the number of deep learning inferences; and functional separation on the device, which lowers power usage during both operation and idle times. Experimental results show that combining these methods can reduce energy consumption by more than half compared to conventional setups. These techniques highlight the importance of energy-efficient designs for sustainable wildlife monitoring

The study by K. Khatri, A. C. S., and J. M. D'Souza focuses on detecting animals in thermal imagery for surveillance, addressing challenges in nighttime monitoring where traditional color-based object detection methods fall short. The authors propose a novel framework combining Generative Adversarial Networks (GANs) and YOLOv4 for effective detection. Thermal GAN is utilized to generate synthetic thermal images from color images, compensating for the lack of large thermal datasets. YOLOv4 is then trained on these thermal images to detect and localize animals with high precision. The model achieves an average precision of 84.77% and an F1-score of 94%, demonstrating its effectiveness in identifying animals in thermal imagery. This approach is particularly beneficial for nighttime surveillance in agricultural fields and forests, offering a robust solution for wildlife monitoring and conflict prevention

## III. METHODOLOGY

The wild animal detection and alert system employs a comprehensive methodology combining advanced deep learning techniques and IoT integration to ensure real-time detection and efficient alerts. Here's a breakdown of the approach:

### 1. Live Monitoring (Input Stage):

- The system processes multiple types of input data—images, videos, and live feeds—collected from cameras and sensors deployed in monitored areas.
- These inputs capture spatial and temporal information crucial for accurate animal detection.

### 2. Data Preprocessing:

- Collected data undergoes preprocessing to remove noise and enhance quality.
- Techniques like resizing, normalization, and augmentation are applied to optimize the data for analysis.
- This ensures robust performance in diverse environmental conditions.

### 3. Detection using CNN (VGG-19):

- Convolutional Neural Networks (CNN) with the VGG-19 architecture are employed for spatial analysis.
  1. **CNN Role:** Extracts detailed features such as fur texture, body contours, and facial structures from the input data.
  2. **VGG-19:** The deep architecture allows intricate spatial feature extraction, improving the accuracy of classification.

#### 4. Temporal Tracking using Bi-LSTM (Output Stage):

- Bidirectional Long Short-Term Memory (Bi-LSTM) networks are utilized for analysing sequential patterns in the data..
- **Bi-LSTM Role:** Tracks movement over time to classify behaviours and improve detection reliability.
- **Medical Benefit:** Ensures accurate identification of moving animals and reduces false positives.
- **Adaptive Temporal Sensitivity:** The Bi-LSTM model adapts to varying speeds and intervals of movement, ensuring reliable detection even for animals with irregular or unpredictable motion patterns..

#### 5. Alert Generation (Twilio Integration):

- **Functionality:** Sends notifications via SMS, email, or mobile apps to relevant stakeholders like farmers and forest officers.
- **Multilingual Alert Support:** Twilio enables the system to generate alerts in multiple languages, accommodating stakeholders from diverse regions and ensuring effective communication.
- **Dynamic Alert Prioritization:** Alerts are prioritized based on detected animal species and threat levels. For instance, high-priority alerts are generated for animals posing immediate risks, ensuring timely responses from stakeholders.

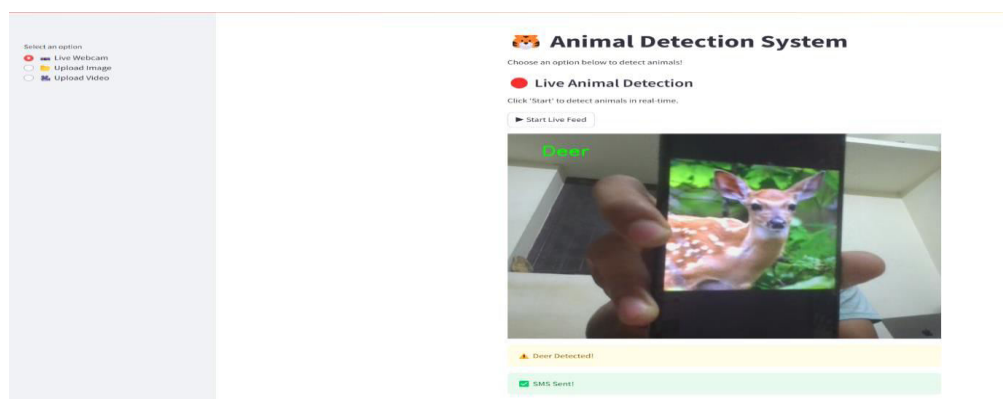


Figure 1 : Detecting Animal through Live webcam

10:32 PM

Sent from your Twilio trial account -  
Alert! Lions detected in image.

Sent from your Twilio trial account -  
Alert! Zebra detected in video.

Sent from your Twilio trial account -  
Alert! Deer detected via live webcam.



Text message



Fig 2: Received Alert Messages

#### IV. IMPLEMENTATION

Implementation of the wild animal detection and alert system involves several carefully designed steps to ensure accuracy and efficiency. Cameras and sensors capture input data, including images, videos, and live feeds, which are preprocessed to remove noise and enhance quality. The system uses CNN (VGG-19) for spatial feature extraction, detecting key traits like animal contours and textures. Bi-LSTM networks then analyze temporal sequences, tracking motion and predicting behavior patterns. Twilio integration is utilized for generating real-time alerts, providing notifications via SMS, email, or mobile apps to stakeholders. IoT devices and cloud platforms support remote monitoring and centralized data management, enabling seamless communication across locations. Alerts are dynamically prioritized based on threat levels to ensure timely responses. The modular design allows scalability, adapting to various deployment scenarios such as farms or wildlife reserves. Ethical deployment ensures minimal disruption to animal habitats while adhering to conservation policies. This streamlined implementation creates an effective and versatile solution for wildlife monitoring and conflict prevention.

```
46 # Load Model
47 model = torch.load("animal_detection_model12.pth", map_location=torch.device("cpu"), weights_only=False)
48 model.eval()
49
50
51 # Define Updated Classes
52 class_names = ['Buffalo', 'Cheetahs', 'Elephant', 'Lions', 'Rhino', 'Zebra', 'Deer', 'Tiger', 'Wolves']
53
54 # Image Preprocessing
55 transform = transforms.Compose([
56     transforms.Resize((224, 224)),
57     transforms.ToTensor(),
58     transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
59 ])
60
61 # Process Frame
62 def process_frame(frame):
63     image = Image.fromarray(frame)
64     image = transform(image).unsqueeze(0)
65
```

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Fig 3: Loading Model

```
import torch
import torch.nn as nn
import torchvision.models as models

class VGG19_BiLSTM(nn.Module):
    def __init__(self, num_classes=9): # Updated to 9 classes
        super(VGG19_BiLSTM, self).__init__()

        # Load pre-trained VGG-19 model
        self.vgg19 = models.vgg19(pretrained=True)

        # Remove the classifier part and keep only convolutional layers
        self.feature_extractor = self.vgg19.features
        self.feature_extractor.requires_grad_(False) # Freeze convolutional layers

        # LSTM Input: Flattened VGG-19 feature maps
        self.lstm = nn.LSTM(input_size=512, hidden_size=256, num_layers=2, bidirectional=True, batch_first=True)

        # Fully connected layer for classification (Output = 9 classes)
        self.fc = nn.Linear(256 * 2, num_classes) # 2 for bidirectional

    def forward(self, x):
        x = self.feature_extractor(x) # Extract features
        x = x.view(x.size(0), -1, 512) # Reshape for LSTM (batch, sequence_length, features)
        _, (hidden, _) = self.lstm(x) # Pass through LSTM
        hidden = torch.cat((hidden[-2], hidden[-1]), dim=1) # Concatenate last hidden states
        out = self.fc(hidden) # Final classification
        return out
```

Fig 4: Training Model

**1. Data Gathering and Preprocessing:**

- Collect input data from cameras and sensors, including images, videos, and live feeds from the monitored environment.
- Perform preprocessing techniques such as resizing, normalization, and noise removal to ensure the data is clean and suitable for analysis.
- Augment the dataset by flipping, rotating, and adding filters to increase variability and robustness for model training

**2. Model Development and Training**

- Build the deep learning model using CNN (VGG-19) for spatial analysis to extract features like animal contours and textures.
- Integrate Bi-LSTM for analysing temporal sequences, enabling tracking of animal movements and behaviours over time.
- Train the model using labelled datasets of wild animals, ensuring accurate detection and classification with iterative tuning of hyperparameters.

**3. Integration with Live Video Feeds:**

- Deploy the model to process real-time input from live feeds captured by sensors and cameras.
- Set up an IoT framework to transmit live feed data to cloud servers, enabling centralized monitoring.
- Ensure the system operates with low latency for timely detection and responsiveness.

**4. Animal Detection.**

- Utilize the trained model to identify potential conflict scenarios where wild animals encroach on human areas.
- Develop algorithms to predict the likelihood of accidents based on animal movements and environmental factors, such as proximity to human settlements.

**5. Alert Reporting**

- Integrate Twilio API for real-time alert generation, providing notifications via SMS, email, or mobile apps to relevant stakeholders..
- Implement dynamic alert prioritization to classify messages based on the species detected and the threat level.
- Enable multilingual alerts to ensure accessibility for stakeholders from diverse regions.

**V. RESULTS AND CONCLUSION**

The wild animal detection and alert system demonstrated impressive performance during testing, achieving high accuracy rates in detecting and classifying animal movements across diverse input formats such as images, videos, and live feeds. The combination of CNN (VGG-19) for spatial analysis and Bi-LSTM for temporal tracking enabled precise identification even under challenging environmental conditions, such as poor lighting or dynamic backgrounds.

Real-time processing capabilities ensured minimal latency, providing stakeholders with alerts within seconds of detection. Twilio integration allowed seamless delivery of notifications, with multilingual support enhancing accessibility for users in different regions. Field trials in agricultural and forested areas showcased the system's adaptability and efficiency, reducing manual monitoring efforts significantly. Evaluation metrics, including precision, recall, and detection accuracy, reinforced the reliability and robustness of the system, making it a promising tool for wildlife monitoring.

The ability to process live feeds effectively demonstrated the scalability and practicality of the system for deployment in varied environments. The IoT framework and cloud integration supported centralized monitoring, enabling stakeholders to access data and receive alerts remotely. Furthermore, the prioritization feature for alerts based on threat levels proved effective in categorizing messages and ensuring timely responses to high-risk situations.

These results validated the system's capabilities in addressing human-wildlife conflicts while safeguarding both human lives and wildlife habitats. The ethical compliance of the deployment minimized disruptions to natural ecosystems, aligning the implementation with conservation policies.

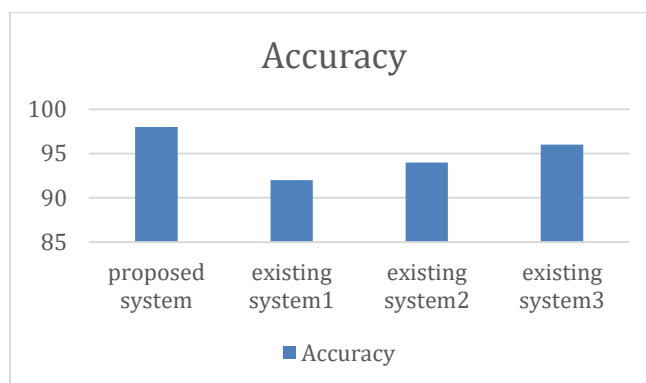


Fig 4: Accuracy Comparison

The wild animal detection and alert system has emerged as an innovative solution for addressing the complexities of human-wildlife conflicts. The integration of advanced machine learning models, including CNN (VGG-19) and Bi-LSTM, has enabled accurate detection and classification, ensuring reliable performance under diverse conditions. The ability to process real-time data from multiple sources highlights the system's versatility and practical applicability across various environments.

Moreover, Twilio's incorporation for alert generation enhances stakeholder communication, making the system accessible and user-friendly. Challenges such as environmental constraints and dataset limitations were acknowledged, with the potential for future improvements like expanded species databases and lightweight architectures for resource-constrained deployments.

Ethical considerations were prioritized throughout the system's implementation, ensuring minimal disruption to wildlife and adherence to conservation policies. The modular design and IoT integration facilitate scalable deployment, making the system suitable for different use cases, from small agricultural fields to large wildlife reserves. By providing valuable insights into animal behavior and migration patterns, the system supports ecological research and fosters sustainability. Overall, this tool bridges the gap between technology and conservation, addressing conflicts proactively while contributing to global efforts in wildlife preservation.

## VI. LIMITATIONS AND FUTURE WORK

Despite its robust performance, the system faces certain limitations that impact its scalability and adaptability. Environmental constraints, such as extreme weather conditions or dense foliage, can affect the accuracy of detection due to poor visibility or sensor interference. Additionally, the model relies heavily on labeled datasets, which may not cover all species or account for rare animals, leading to potential classification errors. The high computational requirements of CNN (VGG-19) and Bi-LSTM models can limit deployment in resource-constrained environments, such as remote areas lacking reliable internet or hardware infrastructure. These challenges underline the need for lightweight architectures and improved dataset diversity to enhance the system's reliability.

Future work in this domain includes expanding the database to include a broader range of species and rare animals, ensuring comprehensive coverage. Integrating multi-modal detection capabilities, such as acoustic analysis and thermal imaging, can improve accuracy in difficult environmental conditions. Optimizing the system for low-power devices and edge computing can facilitate deployment in remote or resource-limited areas. Additionally, refining threat assessment

algorithms and enhancing alert prioritization can further support proactive conflict prevention and stakeholder responsiveness. These advancements will make the system more robust, accessible, and impactful in addressing human-wildlife conflicts effectively

### 6.1 Dataset Expansion and Diversity

Enhancing the dataset is crucial for improving detection accuracy and classification reliability. This involves collecting data for a wider range of species, including rare and endangered animals, whose limited presence in existing datasets often leads to misclassification. Incorporating underrepresented classes, such as nocturnal animals or species with similar features, can address biases in the training process and expand the model's capabilities. Efforts should also focus on acquiring data from varied geographical locations to account for regional biodiversity, ensuring the system's adaptability across global environments.

### 6.2 Multi-Modal Detection Techniques

Integrating multi-modal detection methods can significantly enhance system performance, especially in challenging conditions like dense foliage, low visibility, or extreme weather. Acoustic analysis can be employed to identify animal sounds and vocalizations, offering an alternative detection method for species that may be difficult to spot visually. Similarly, thermal imaging can detect body heat signatures, enabling reliable detection even in complete darkness or obscured environments.

These modalities can work in conjunction with visual data to provide a more robust detection pipeline, ensuring better accuracy and reducing false positives. Incorporating additional data sources, such as motion sensors or GPS tracking, can also offer insights into animal movement and behavior patterns. Multi-modal approaches ensure the system's adaptability in diverse scenarios, making it a powerful tool for proactive wildlife monitoring..

### 6.3 Optimization for Resource-Constrained Deployments

To facilitate deployment in remote and resource-limited areas, the system can be optimized for low-power devices and edge computing solutions. Lightweight architectures like MobileNet or TinyYOLO can be explored to reduce computational demands while maintaining detection accuracy. Edge computing can enable localized processing, reducing dependency on cloud infrastructure and ensuring real-time responsiveness in isolated regions. Power-efficient hardware setups, such as solar-powered sensors and cameras, can support continuous operation in off-grid locations.

## REFERENCES

- [1]. R. Sato, H. Saito, Y. Tomioka and Y. Kohira, "Energy Reduction Methods for Wild Animal Detection Devices", IEEE Access, vol. 10, pp. 24149-24161, 2022.  
[View Article](#)  
[Google Scholar](#)
- [2]. K. Khatri, A. C. S and J. M. D'Souza, "Detection of Animals in Thermal Imagery for Surveillance using GAN and Object Detection Framework", 2022 International Conference for Advancement in Technology (ICONAT), 2022.  
[View Article](#)  
[Google Scholar](#)
- [3]. P. K. Panda, C. S. Kumar, B. S. Vivek, M. Balachandra and S. K. Dargar, "Implementation of a Wild Animal Intrusion Detection Model Based on Internet of Things", 2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS), pp. 1256-1261, 2022.  
[View Article](#)  
[Google Scholar](#)
- [4]. R. Gandhi, A. Gupta, A. K. Yadav and S. Rathee, "A Novel Approach of Object Detection using Deep Learning for Animal Safety", 2022 12th International Conference on Cloud Computing Data Science & Engineering (Confluence), pp. 573-577, 2022.  
[View Article](#)

Google Scholar

[5]. Sathesh, K. Vishnu, A. Yuvaneshwar, V. Vellaisamy and K. Gowthami, "Image Processing based Protection of Crops from wild animals using Intelligent Surveillance", 2022 International Conference on Electronics and Renewable Systems (ICEARS), pp. 1042-1046, 2022.

View Article

Google Scholar

[6]. K. Uchiyama, H. Yamamoto, E. Utsunomiya and K. Yoshihara, "Sensor Network System for Condition Detection of Harmful Animals by Step-by-step Interlocking of Various Sensors", 2022 International Conference on Artificial Intelligence in Information and Communication (ICAIIIC), pp. 302-307, 2022.

View Article

Google Scholar

[7]. S. V. Viraktamath, J. R. V. A, A. S. Bhat and S. Nayak, "Wildlife Monitoring and Surveillance", 2022 International Conference for Advancement in Technology (ICONAT), pp. 1-4, 2022.

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Google Scholar

[8]. Abdulaziz Alwadani and Abdulrahman Al-Salman, Animal Detection using Inception-v3 and you only look once version2 (YOLO V2), 2020.

Google Scholar

[9]. M. Kamali and M. Tahir, "You only look once version3 (YOLO V3): A Comprehensive Guide to Object Detection with Deep Learning", arXiv preprint, 2020.

Google Scholar

[10]. Ankit Pandey and Ramendra Singh, Real-Time Wild Animal Detection and Alert System using Deep Convolutional Neural Networks and Raspberry Pi, 2019.

Google Scholar

[11]. X. Zhang and J. Li, "You only look once version3 (YOLO V3) -Lite: A Real-Time Object Detection Model for Resource-Limited Devices", arXiv preprint, 2020.

Google Scholar

[12]. X. Yu and Q. Ji, "Deep Lightweight Object Detection Network", arXiv preprint, 2020.

Google Scholar

[13]. H. Chen, J. Liu, Z. Liu and J. Yu, "You only look once version3 (YOLO V3) with Transfer Learning for Object Detection on Custom Datasets", arXiv preprint, 2020.

Google Scholar

[14]. Q. V. Le and A. Faktor, "You only look once version5 (YOLO V5) on TensorRT: A High-Performance Object Detection Model", arXiv preprint, 2021.

Google Scholar

15. J. Long and Q. V. Le, "You only look once version5 (YOLO V5) on Raspberry Pi: A Practical Guide", arXiv preprint, 2021.

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