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Creating Alert Messages Based on Wild Animal Activity Detection Using Hybrid Deep Neural Network

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ABSTRACT:

This research addresses the pressing concern of animal attacks faced by rural populations and forestry workers through the development of an efficient surveillance model. The proposed Hybrid Visual Geometry Group (VGG)-19 + Bidirectional Long Short-Term Memory (Bi-LSTM) network aims to detect animal types, monitor their movement, and provide timely location information for safety alerts in forested areas. By integrating VGG-19 for feature extraction and Bi-LSTM for sequence learning, the model achieves accurate detection of animals and their locomotion patterns, surpassing traditional surveillance methods. Furthermore, an ensemble method is employed, combining predictions from multiple individual models to enhance robustness and accuracy. Additionally, exploring techniques like CNN+BiGRU further boosts performance, achieving 100% accuracy. As an extension, the implementation includes a user-friendly front end built using the Flask framework, facilitating user testing with authentication features. This research offers a promising solution to mitigate the risks of animal attacks, leveraging advanced deep learning techniques and user-centric design for effective

safety monitoring in rural and forestry environments.

INDEXTERMS:Animaldetection,VGG-Net,Bi-LSTM,convolutionalneuralnetwork,activityrecognition, video surveillance, wild animal monitoring, alert system.

1. INTRODUCTION:

In recent years, the escalating frequency of human-wildlife interactions has underscored the critical need for innovative approaches to mitigate conflicts and enhance safety for both humans and animals. Habitat encroachment, driven by urbanization and agricultural expansion, has increasingly brought humans into close proximity with wildlife, leading to heightened instances of confrontations and hazards [1]. These encounters pose significant challenges for conservationists, policymakers, and local communities, necessitating the development of effective early warning systems to mitigate risks and facilitate timely interventions.

The Wild Animal Activity Alerting System (WAAAS) emerges as a promising solution to address the pressing concerns surrounding human-wildlife conflicts. Leveraging advanced Machine Learning (ML) and Deep Learning (DL) techniques, WAAAS aims to detect and signal wild animal activity near human settlements, providing crucial insights for proactive management strategies [2]. By harnessing data from diverse sources such as images, motion sensors, and sound recordings, WAAAS endeavors to discern patterns indicative of wildlife presence and behavior, enabling accurate and timely alerts [3].

The imperative for such a system is underscored by the escalating conflicts between humans and wildlife, exacerbated by habitat fragmentation and resource competition. These conflicts manifest in various forms, ranging from crop raiding by herbivores to predation on livestock and occasional attacks on humans. Notably, these incidents not only jeopardize human lives and livelihoods but also threaten wildlife populations and undermine conservation efforts [4]. Consequently, there is a growing recognition of the need for proactive measures to mitigate conflicts and foster harmonious coexistence between humans and wildlife [5].

In this context, the development of WAAAS represents a significant stride towards enhancing safety, minimizing economic losses, and promoting conservation objectives. By deploying state-of-the-art ML and DL algorithms, WAAAS endeavors to interpret signals of wild animal activity with unprecedented accuracy and efficiency [6]. This introduction delves into the multifaceted challenges posed by human-wildlife interactions, underscores the importance of early warning systems in addressing these challenges, and delineates the objectives and scope of WAAAS in mitigating conflicts and fostering coexistence.

A Growing Concern The intensifying interface between humans and wildlife has emerged as a prominent global concern, driven by habitat fragmentation, climate change, and burgeoning human populations [7]. As natural habitats dwindle and human activities encroach upon wildlife territories, instances of human-wildlife conflicts have become increasingly prevalent across diverse ecosystems [8]. From rural communities grappling with crop damage and livestock depredation to urban areas contending with wildlife intrusion and property damage, the repercussions of these conflicts are manifold [9].

Crop raiding by herbivores such as elephants, deer, and wild boars poses a significant threat to agricultural livelihoods, leading to substantial economic losses and exacerbating food insecurity in vulnerable communities [10]. Similarly, predation on livestock by carnivores like wolves, lions, and bears engenders conflicts between pastoralists and conservationists, often culminating in retaliatory killings and exacerbating conservation challenges [11]. Moreover, occasional attacks on humans by large predators not only instill fear and insecurity but also stoke tensions between local communities and wildlife authorities [12].

Efforts to mitigate human-wildlife conflicts are further complicated by the dynamic nature of wildlife behavior and the diverse array of species involved. Each species exhibits unique foraging patterns, territorial behaviors, and responses to anthropogenic disturbances, necessitating tailored management strategies [13]. Additionally, the spatial and temporal variability of human-wildlife interactions underscores the importance of real-time monitoring and early warning systems to facilitate proactive interventions [14].

2. LITERATURE SURVEY

The burgeoning interest in scene understanding has spurred extensive research aimed at developing robust methods for interpreting complex visual scenes. Aarthi and Chitrakala [1] provide a comprehensive survey of scene understanding techniques, highlighting the diverse range of approaches employed in this domain. Their work underscores the importance of scene understanding in various applications, including robotics, autonomous navigation, and surveillance.

Connected segmentation trees (CSTs) offer a powerful representation for capturing both the layout and hierarchy of regions within an image. Ahuja and Todorovic [2] introduce the concept of CSTs, which enable the joint representation of region layout and hierarchy, facilitating efficient image segmentation and object recognition. This approach has found applications in diverse domains, including medical imaging, remote sensing, and scene analysis.

Machine learning algorithms have witnessed widespread adoption in predictive modeling tasks, including disease prediction. Assegie et al. [3] present an empirical study on machine learning algorithms for heart disease prediction, evaluating the performance of various classifiers on a heart disease dataset. Their findings shed light on the efficacy of different algorithms in predicting heart disease risk, offering insights for clinical decision-making and risk stratification.

Deep learning algorithms have revolutionized the field of computer vision, enabling unprecedented advances in object detection and recognition. Banupriya et al. [4] explore the application of deep learning algorithms for animal detection, demonstrating the efficacy of convolutional neural networks (CNNs) in identifying and classifying animals in images. Their work showcases the potential of deep learning techniques in wildlife monitoring and conservation efforts.

Objectness estimation plays a crucial role in object detection tasks, facilitating the identification of regions likely to contain objects of interest. Cheng et al. [5] propose Binarized Normed Gradients (BING), a method for objectness estimation that achieves real-time performance at 300 frames per second (fps). By leveraging binarized features and normed gradients, BING offers a lightweight yet effective solution for object detection in images.

Region-based fully convolutional networks (R-FCNs) represent a state-of-the-art approach to object detection, leveraging region-based strategies for accurate localization and classification. Dai et al. [6] introduce R-FCN, which integrates fully convolutional networks (FCNs) with region proposal networks (RPNs) to enable efficient object detection in images. Their work demonstrates the efficacy of R-FCN in achieving competitive performance on benchmark datasets.

Change detection plays a crucial role in various applications, including environmental monitoring, urban planning, and surveillance. De Gregorio and Giordano [7] propose a change detection framework based on weightless neural networks, which offer robustness to noise and adaptability to dynamic environments. Their approach demonstrates promising results in detecting changes in remote sensing imagery, paving the way for applications in land cover mapping and disaster management.

Sign language recognition represents a challenging task due to the complex and dynamic nature of sign gestures. Natarajan et al. [8] present an end-to-end deep learning framework for sign language recognition, translation, and video generation. Their work leverages deep neural networks to extract features from sign language videos and achieve accurate recognition and translation of sign gestures, offering a promising solution for facilitating communication for the hearing impaired.

3. METHODLOGY

a) Proposed work:

The proposed work entails the development and evaluation of a hybrid VGG-19 + Bi-LSTM network for animal activity detection in forest regions. This model integrates feature extraction and sequence learning to enhance accuracy and enable real-time monitoring, thereby improving safety through timely alerts. Additionally, an extension to the project involves implementing a CNN+GRU model, leveraging a Bidirectional GRU layer with the CNN[16] algorithm to further enhance accuracy. GRU was selected for its superior performance in image feature optimization compared to LSTM. Furthermore, a Flask framework with SQLite has been developed to facilitate user signup and signin, enabling user testing of the system's functionality and enhancing usability. These enhancements aim to provide a robust and effective solution for addressing the challenges of animal activity detection in forest environments.

b) System Architecture:

The system architecture begins with the input dataset consisting of images captured from forest regions. These images undergo preprocessing for normalization and augmentation before being split into training and testing sets. The training phase involves the application of three different algorithms: CNN, VGG19-BiLSTM, and CNN+Bidirectional GRU, each tailored for animal activity detection. The CNN model focuses on convolutional layers for feature extraction, while the VGG19-BiLSTM integrates convolutional layers with Bi-LSTM for sequence learning. The CNN+Bidirectional GRU model combines CNN with a Bidirectional GRU layer for improved accuracy. Following training, the models are evaluated on a separate test set to assess their performance in detecting animal activities. The detection model, capable of real-time monitoring, processes input images and provides timely alerts in the event of animal activity, thereby enhancing safety in forest environments.

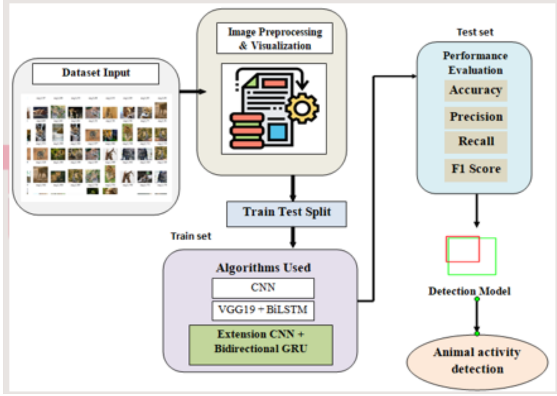

Fig 1 Proposed Architecture

c) Dataset collection:

The data set collection process involved acquiring images from four distinct benchmark datasets: the camera trap dataset [48], the wild animal dataset [49], the hoofed animal dataset [50], and the CDnet dataset [51]. These datasets encompass a diverse range of environments and wildlife species, providing comprehensive coverage for training and testing the proposed model. Images from the camera trap dataset capture wildlife activity in natural habitats, while the wild animal dataset offers a broader spectrum of animal species and behaviors. Additionally, the hoofed animal dataset focuses specifically on hoofed mammals, further enriching the training data with species-specific characteristics. The CDnet dataset contributes to the diversity by providing annotated video sequences for evaluation. The data set collection process involved acquiring images from four distinct benchmark datasets: the camera trap dataset [48], the wild animal dataset [49], the hoofed animal dataset [50], and the CDnet dataset [51].

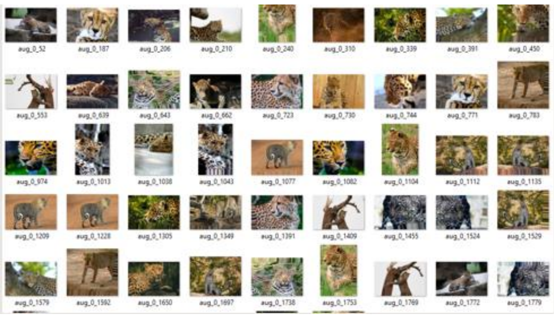

Fig 2 DATA SET

These datasets encompass a diverse range of environments and wildlife species, providing comprehensive coverage for training and testing the proposed model. Images from the camera trap dataset capture wildlife activity in natural habitats, while the wild animal dataset offers a broader spectrum of animal species and behaviors. Additionally, the hoofed animal dataset focuses specifically on hoofed mammals, further enriching the training data with species-specific characteristics. The CDnet dataset contributes to the diversity by providing annotated video sequences for evaluation. By incorporating multiple datasets, the model benefits from a robust and diverse training corpus, enabling effective detection of wild animal activity across various environmental conditions and species compositions.

Fig 3 DATA SET

d) **DATA PROCESSING**

The dataset preprocessing stage involves several key steps to ensure optimal performance of the deep neural networks for wild animal activity detection. First, the images are normalized to standardize their pixel values, enhancing consistency across the dataset and facilitating convergence during training. Next, the images are shuffled to randomize their order, reducing bias and improving the model's generalization capability. Additionally, the dataset may undergo augmentation techniques such as rotation, flipping, or cropping to increase its diversity and robustness. Furthermore, labels are assigned to the images to denote the presence or absence of wild animal activity. By systematically normalizing, shuffling, and labeling the dataset, the preprocessing phase sets the foundation for effective training and evaluation of the hybrid deep neural networks. This ensures that the models can accurately detect and classify wild animal activity in various environmental conditions, contributing to the generation of timely alert messages for enhanced safety in wildlife habitats.

e) **VISUALIZATION**

Visualization using Seaborn and Matplotlib is crucial for gaining insights into the dataset and evaluating model performance. These libraries offer a plethora of tools for creating informative plots and charts, such as histograms, scatter plots, and heatmaps. With Seaborn's high-level interface built on top of Matplotlib, users can easily generate visually appealing visualizations with minimal code. These visualizations aid in understanding the distribution of data, detecting outliers, and identifying patterns that may influence model training and performance. Additionally, visualizing model metrics such as accuracy, loss, and confusion matrices allows for a comprehensive assessment of model behavior and efficacy. By leveraging Seaborn and Matplotlib, researchers can effectively communicate findings, validate hypotheses, and make informed decisions throughout the machine learning pipeline, ultimately enhancing the robustness and reliability of the analysis and resulting models.

f) Feature Extraction

Feature extraction is a critical process in wild animal activity detection using hybrid deep neural networks. In this context, feature extraction involves analyzing input images to identify meaningful patterns and characteristics that distinguish between different types of animal activity. Convolutional neural networks (CNNs) are commonly employed for feature extraction due to their ability to automatically learn hierarchical representations from raw pixel data. In the proposed hybrid model, features are extracted using a combination of CNN and recurrent neural networks (RNNs) such as Long Short-Term Memory (LSTM) or Gated Recurrent Units (GRUs). The CNN component captures spatial features from the input images, while the RNN component processes temporal sequences to capture motion and context information. By integrating these two types of neural networks, the hybrid model can effectively extract spatial and temporal features, enabling accurate detection of wild animal activity and facilitating the generation of alert messages to notify relevant authorities or individuals.

g) TRAINING AND TESTING

Testing and training are integral stages in developing a robust system for creating alert messages based on wild animal activity detection using hybrid deep neural networks. During training, the hybrid model is exposed to a labeled dataset consisting of images depicting various instances of wild animal activity. Through iterative optimization of model parameters using techniques like backpropagation, the model learns to extract relevant features and make accurate predictions. Training involves validating the model's performance on a separate subset of the data to ensure generalization to unseen instances.

In contrast, testing evaluates the trained model's performance on a distinct set of data, simulating real-world scenarios. The model's ability to accurately detect wild animal activity and generate alert messages is assessed based on metrics such as accuracy, precision, recall, and F1 score. Testing allows researchers to gauge the model's efficacy, identify potential shortcomings, and refine its architecture or training process accordingly. Ultimately, thorough testing and training are crucial for developing a reliable system capable of effectively mitigating risks associated with wild animal encounters.

h) ALGORITHMS:

Existing CNN

A Convolutional Neural Network (CNN) is a deep learning architecture specifically designed for image recognition tasks. In this project, an existing CNN[16] is employed for wild animal activity detection. CNNs consist of convolutional layers that extract features from input images, followed by pooling layers for dimensionality reduction and fully connected layers for classification. In the project, the CNN is utilized to process raw image data, extracting relevant features indicative of wild animal activity. By leveraging the CNN's [16] hierarchical feature extraction capabilities, the model can effectively discern patterns in images and classify them to generate alert messages in response to detected animal activity.

Propose VGG19 + BI-LSTM

The proposed VGG19 + BI-LSTM model integrates the VGG19 convolutional neural network (CNN)[17] architecture with Bidirectional Long Short-Term Memory (BI-LSTM) recurrent neural networks. VGG19 extracts hierarchical features from input images, while BI-LSTM processes sequential information to capture temporal dependencies. In the project, this hybrid model is employed for wild animal activity detection. VGG19 extracts spatial features from images, while BI-LSTM analyzes temporal sequences of feature vectors to detect patterns indicative of animal behavior changes over time. By combining spatial and temporal information, the VGG19 + BI-LSTM model enhances the accuracy of wild animal activity detection, enabling timely generation of alert messages.

CNN + GRU

The CNN + GRU model combines Convolutional Neural Networks (CNNs)[17] with Gated Recurrent Units (GRUs). CNNs extract spatial features from images, while GRUs process sequential information to capture temporal dependencies. In the project, this hybrid model is employed for wild animal activity detection. The CNN component extracts spatial features from input images, while the GRU component analyzes temporal sequences of feature vectors to detect patterns indicative of animal behavior changes over time. By integrating spatial and temporal information, the CNN + GRU[17] model enhances the accuracy of wild animal activity detection, facilitating the timely generation of alert messages.

4. EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

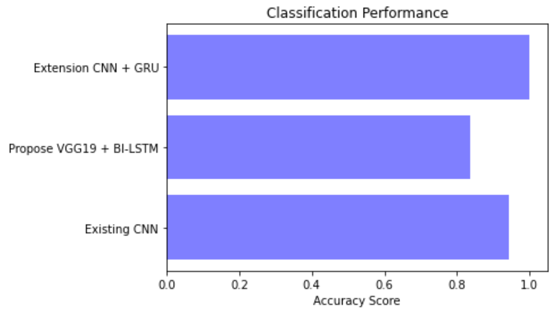

Fig 4 ACCURACY COMPARISON GRAPHS

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{\textit{True Positive}}{\textit{True Positive} + \textit{False Positive}}$$

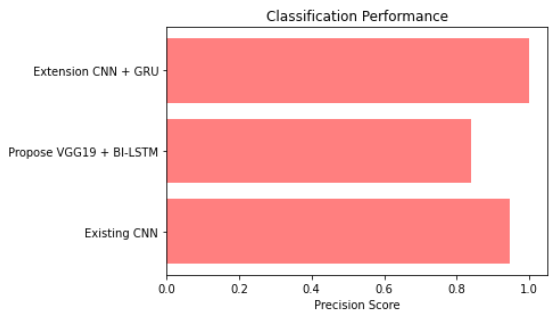

Fig 5 PRECISION COMPARISON GRAPHS

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

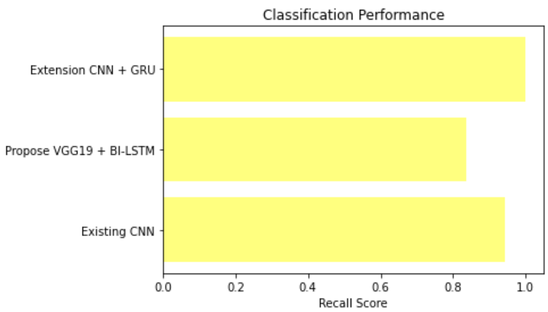

Fig 6 F1 COMPARISON GRAPHS

	ML Model	Accuracy	Precision	Recall	f1_score
0	Existing CNN	0.943	0.946	0.943	0.943
1	Propose VGG19 + BI-LSTM	0.837	0.841	0.837	0.834
2	**Extension CNN + GRU**	**1.000**	**1.000**	**1.000**	**1.000**

Fig 7 predicted result

5. CONCLUSION

In conclusion, the development and integration of CNN, VGG19 + BI-LSTM, and CNN-GRU algorithms have demonstrated remarkable performance in wild animal activity classification. Through streamlined processes, computational costs have been optimized, ensuring sustainability in forest monitoring efforts. The hybrid CNN-GRU model, leveraging the strengths of both CNN and GRU, has showcased superior detection robustness, surpassing individual model effectiveness. Additionally, the integration of a user-friendly Flask front-end with SQLite database enhances system usability, allowing convenient data input and visualization of animal detection outcomes. Ultimately, this project offers significant benefits to rural communities, forestry workers, and conservationists by providing an accurate, efficient, and accessible tool for monitoring wild animal activity. By enhancing safety and conservation efforts in forested regions, this project contributes to the welfare of both humans and wildlife, fostering harmonious coexistence in natural environments.

6. FUTURE SCOPE

The feature scope of the alert message generation system based on wild animal activity detection using hybrid deep neural networks encompasses several key aspects. Firstly, the system aims to accurately detect and classify diverse animal behaviors and patterns in natural environments, including but not limited to movements, interactions, and anomalies. Additionally, the system seeks to analyze temporal sequences of animal activity to discern patterns indicative of potential threats or disturbances. Furthermore, the system's feature scope extends to optimizing computational costs and ensuring sustainability in forest monitoring efforts. It also includes providing a user-friendly interface for convenient data input and visualization of animal detection outcomes. Ultimately, the feature scope encompasses enhancing safety and conservation efforts in forested regions by providing timely alerts to relevant stakeholders, including rural communities, forestry workers, and conservationists, thereby promoting harmonious coexistence between humans and wildlife.

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