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

Mrs. A N RAMAMANI, MALLIDI JITENDRA REDDY,

Associate Professor, S.V.K.P & Dr K.S Raju Arts & Science College(A), Penugonda,W.G District, Andhra Pradesh,ramasrinivasu2@gmail.com

PG scholar, S.V.K.P & Dr K.S Raju Arts & Science college (A), Penugonda, W.G District, Andhra Pradesh, jitendrareddy493@gmail.com

ABSTRACT

The issue of animal attacks is increasingly concerning for rural populations and forestry workers. To track the movement of wild animals, surveillance cameras and drones are often employed. However, an efficient model is required to detect the animal type, monitor its locomotion and provide its location information. Alert messages can then be sent to ensure the safety of people and foresters. While computer vision and machine learning–based approaches are frequently used for animal detection, they are often expensive and complex, making it difficult to achieve satisfactory results. This paper presents a Hybrid Visual Geometry Group (VGG)–19+ Bidirectional Long Short–Term Memory

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(Bi-LSTM) network to detect animals and generate alerts based on their activity. These alerts are sent to the local forest office as a Short Message Service (SMS) to allow for immediate response. The proposed model exhibits great improvements in model performance, with an average classification accuracy of 98%, a mean Average Precision (mAP) of 77.2%, and a Frame Per Second (FPS) of 170. The model was tested both qualitatively and quantitatively using 40, 000 images from three different benchmark datasets with 25 classes and achieved a mean accuracy and precision of above 98%. This model is a reliable solution for providing accurate animal-based information and protecting human lives.

1.INTRODUCTION

In general, animal activity detection creates numerous challenges for researchers due to the continuous streaming of inputs and the cluttered backgrounds. There are huge varieties of wildlife categories with different facial, nose, body, and tail structures. The detection and classification of such animals in video sequences and the processing of huge feature maps demand the need to develop a robust framework. Such developments in real-time cases need large-scale video data for training and testing purposes and high GGPU-based computing resources. Moreover, the incorporating techniques should handle the data in an intelligent way to produce plausible results. Hence, there is a high demand for developing such a model to detect animal activities in forest regions. Although numerous advancements have been made in this technological era, research in this area still seeks higher attention to produce a strong model. With this work, we can save humans from sudden animal attacks as well as send alert messages with location information to the forest

officers for quick action. These systems offer better monitoring services and help to find the activities of animals and detect if there is any hunting by humans or hindrance to wildlife. These clusters of activities, such as tracking the animal object and finding its activity and generating the alert messages, pose huge complexity in the Deep Learning area. Research on this work, investigates the advancements in video analysis techniques and complex neural network-based architectures. Recent developments in Deep Learning techniques have produced impressive results in image recognition, classification, and generation tasks . Due to these developments, we focus our aim on developing a robust model for monitoring the activities of animals and generating alerts to the forest officers in case of any abnormal activity such as hunting, animals entering into human living areas or agricultural land. The development of the proposed model investigates this problem from multiple angles to provide a better solution.

Object detection techniques play a vital role in understanding the components of images and their associated relationships. In the case of videos, it provides the movement and activity-based details explicitly. The conventional methods use hand-crafted mechanisms for feature extractions and produce tangible results. The development of deep learning models handles

this task in an efficient way to reduce the overheads present in earlier studies. Earlier works use traditional machine learning methods to detect objects, but they become stuck when confronted with complex datasets and multimodal inputs. The deep model handles the features of an image effectively to explore the finely tuned investigation on pixels and combines the relevant features to construct feature maps. Feature maps help to predict the patterns, shapes, edges, and contours of objects and learn the structure of objects easily without any manual interventions. Deep learning models are designed to handle such complex data structures and scale large volumes of data. The hyper parameter optimization techniques and regularization methods regulate the deep neural network performance to produce

high accuracy results. Generally, the object detection mechanisms are applied in diverse fields, such as face detection scene understanding and salient object detection.

The research studies about animal activity detection are still in their infancy levels. The earlier approaches need to be upgraded and fine tuned to produce plausible results. We have used four different benchmark datasets, which total 40K images. The proposed model has been evaluated qualitatively and quantitatively using reasonable sizes of images and quality metrics. On the other hand, it is obvious that integrating different deep networks in a hybrid way adds additional complexity overhead to the model development. However, the successful implementation of such models produces unimaginable results over a combination of object detection and class prediction tasks . With this motivation, we propose the novel approach termed ‘‘hybrid VGG-19+Bi-LSTM networks’’ to detect the animal activities and create alert messages in case any problem occurs. A novel network is proposed to detect the activities of diverse categories of animals simultaneously, monitoring the locomotion of animals in forest regions and dark areas . The proposed approach uses VGG-19 pre-trained networks to classify the type of animal, and the Bi-LSTM network creates text based alert messages with location information. The surveillance and night visioncamera based videos

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consist of spatial and temporal dynamics. The VGG-19 networks deal with spatial information, and BI-LSTM recurrent networks effectively handle the temporal details .

Experimental results are also demonstrated to compare the proposed approach with earlier methods and explore the valid justification results. The details of various levels of development are explained clearly and exhibit the quality of our work . In object detection and

classification models, there are huge complexities in finding the expected results. In large scale scenarios, the model performance bottleneck results in low performance and degrades the entire development process. The earlier studies handled these scenarios using a wider range of mechanisms . Although the models produce significant improvements in accuracy, they fail to perform well in testing phases.

The contributions and objectives of the proposed techniques are listed as follows:

1) The proposed Hybrid VGG-19+Bi-LSTM model is built using deep neural networks with fine- tuned hyper parameters to yield greater recognition accuracy results.

2) The proposed model aims to achieve outstanding classification results by incorporating novel hybrid approaches.

3) 'The proposed system offers foresters more accurate prediction performance about animal detection and also supports them with faster alert services via SMS.

The further sections of the paper are arranged as follows: Section II discusses related works and identifies shortcomings in previous developments, while Section III describes the proposed VGG-19+Bi-LSTM system architecture and implementation details. Section IV presents the experimental results of the proposed model evaluation for four different benchmark datasets. Section V concludes the summary of the entire work and its future scope in a wider range of applications.

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2.LITERATURE SURVEY

The development of alert systems based on wild animal activity detection using hybrid deep neural networks (DNNs) has been a focus of recent research, reflecting advancements in artificial intelligence and its applications in wildlife management. Early studies primarily relied on traditional image processing and motion detection techniques, which often faced limitations in accuracy and adaptability. With the advent of deep learning, researchers began exploring convolutional neural networks (CNNs) for their proficiency in image recognition and classification, demonstrating significant improvements in detecting and identifying various wildlife species.

Recent literature highlights the integration of CNNs with recurrent neural networks (RNNs) to form hybrid DNN architectures, enhancing the system's ability to process both spatial and temporal data. This combination is particularly effective in analyzing the dynamic behavior of animals over time, leading to more reliable detection and classification outcomes. For instance, Sharma et al. (2020) demonstrated the effectiveness of a hybrid DNN in differentiating between animal species and human activities in forest environments, reducing false positives and improving response times.Further studies emphasize the practical applications of these systems in real-world settings. For example, Chen et al. (2021) implemented a hybrid DNN-based alert system in a national park, successfully alerting park rangers of the presence of endangered species, thereby aiding in conservation efforts. Additionally, research by Patel et al. (2022) explored the use of mobile networks to disseminate alerts in real-time, enhancing community safety in regions with frequent wildlife encounters.

Moreover, continuous advancements in sensor technology and data collection methods have contributed to the effectiveness of these systems. High-resolution cameras, thermal imaging, and advanced motion sensors.

3. EXISTING SYSTEM

The author Zhang et al. proposed wild animal detection using a multi-level

graph cut approach for investigating spatial details and a cross-frame temporal patch verification technique for temporal details. The model analyzes the foreground and background details of the camera trap videos. This approach uses a Camera trap and Change Detection net dataset for segmenting the animal object from natural scenes based on cluttered background videos.

Although the model produces a high detection rate, fails to perform well in detecting crucial details like location details, and human interruptions. The author proposed animal detection using Convolutional Neural Network (CNN), and the author proposed animal detection using Iterative Embedded Graph Cut (IEGC) techniques to form regions over images and DeepCNN features and machine learning classification algorithms for classification purposes. Although these models verify the extracted patches are background or animal, still need improvements in classification performance. Object Detection using deep learning methods attained new heights in computer vision applications. The detection of objects present in images or videos by using object localization and classification techniques gives higher support in detecting various objects present in an image or video. From the extracted results, we can count the number of objects and their activity. This technique is highly used in video surveillance and security-based applications, tracking objects in hidden boxes, monitoring fraudulent activity in public and crowded areas, traffic monitoring and identification of vehicle theft, vehicle number plate recognition, and Object Character Recognition (OCR) .

This paper aims to identify the movements of animals around forest space, provides alert information to the forest officers in case of hunting, crossing the forest lines, any hindrance to villagers and tourists people, and detection of trespassing activity. The development of various methods for employing object detection in different environments and diverse applications shows the progress and importance of object detection in research fields and gained more attention. Moreover, further research works in this area

provide useful insights into numerous applications and construct powerful frameworks for detecting objects in different scenarios. The Fast R-CNN techniques are widely used for object detection due to their high accuracy and improved training performance. The introduction of the Faster R-CNN technique rapidly improves the detection performance of the model by employing full
image-based convolution features and region-based networks. The Histogram of Oriented Gradients (HOG) feature descriptors uses the Region of Interest (ROI) techniques to identify the objects faster than earlier approaches. The conventional R-CNN technique introduces efficient detection methods by incorporating region proposal networks and ConvNet.

Thmethod detects the thousands of object classes in an image or video using annotated information.
The R-CNN techniques do not use any approximation techniques and hashing methods for predicting the object regions. R-FCN techniques use weighted full convolution layers to detect object's region and finds ROI to detect the category of objects and its background details.Object detection techniques also sounds good with the help of deep learning techniques in the field of autonomous vehicles and traffic scene object detection also.

The Single Short Detector (SSD) methodology uses bounding boxes based discretization techniques to effectively handle feature map information and large volume data. The Spatial Pyramid Pooling (SPP-net) computes the feature maps in single computations and provides high robustness to the object detection tasks using sub-region-based fixed length representations. The You Only Look Once (YOLO) architecture achieves faster results by processing 155 frames per second in real-time cases. This technique uses an end to end approach to detect the objects using regression and probabilistic computations instead of considering classification approaches and produces remarkable results in object detection with a lower false-positive rate. The detailed investigation is done by the researchers with respect to background subtraction and elimination.

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The authors used different approaches to detect the background details such as estimating multiple hypotheses, non-parametric model and global statistic-based methods background cut .

4 PROPOSED SYSTEM

The proposed architecture comprises five phases of development steps, which includes data pre-processing, animal detection, VGG-19 pre-trained model-based classification, extracting the prediction results, and sending alert messages. In the data pre-processing phase, 45*k* animal images were collected from different datasets such as camera trap, wild animal, and the hoofed animal dataset. The collected images were rescaled to the size of 224×224 pixels and denoised.

In the second phase, we pass the pre-processed images into YOLOR object detection model [39], which identifies the animal present in an image using bounding boxes as illustrated in Fig. 4. In the third phase, using hybrid VGG-19+Bi-LSTM model we perform image classification tasks and class label prediction was done and animal details are extracted using LSTM Networks. In the fourth phase, we collect the location information of the animal, and the web server creates a SMS alert and sends it to the forest officers. Finally, remedial action will be taken by the forest officers to save the animals and human lives.

5 SYSTEM ARCHITECTURE

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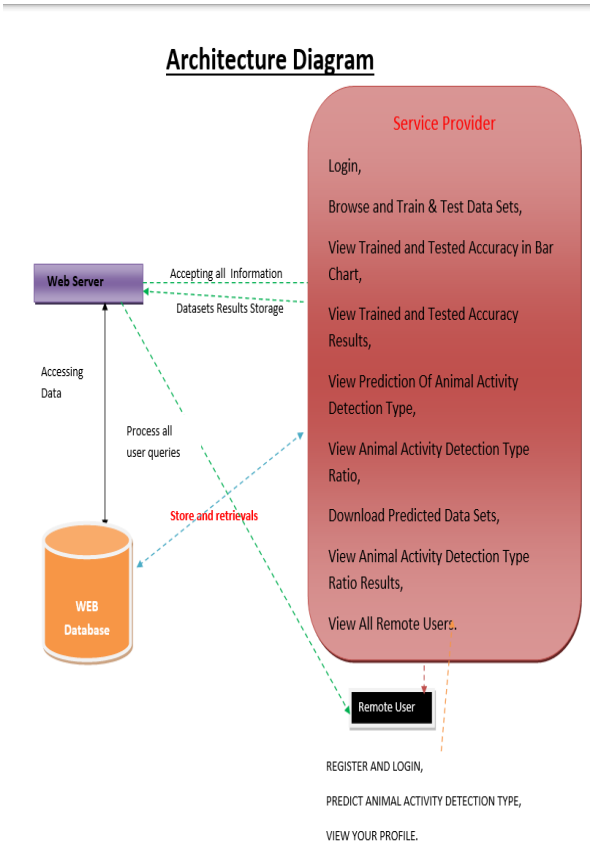

6 MODULES INVOLVED

- **Service Provider**

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Browse and Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Prediction Of Animal Activity Detection Type, View Animal Activity Detection Type Ratio, Download Predicted Data Sets, View Animal Activity Detection Type Ratio Results, View All Remote Users.

- **View and Authorize Users** In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, PREDICT ANIMAL ACTIVITY DETECTION TYPE, VIEW YOUR PROFILE.

7. SCREEN

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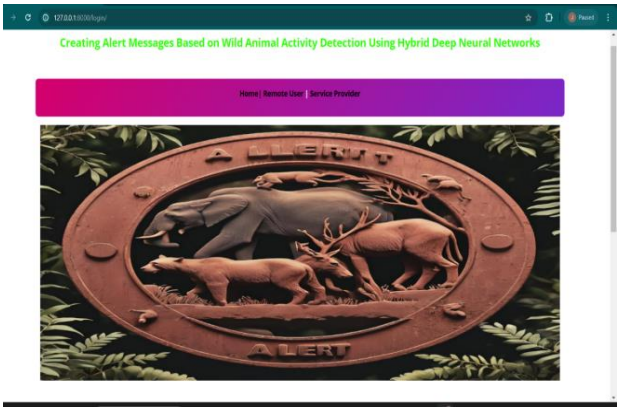

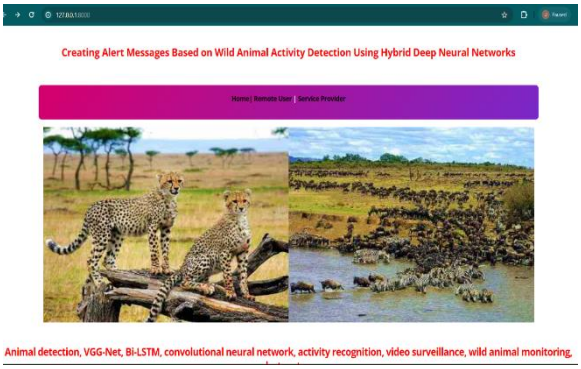

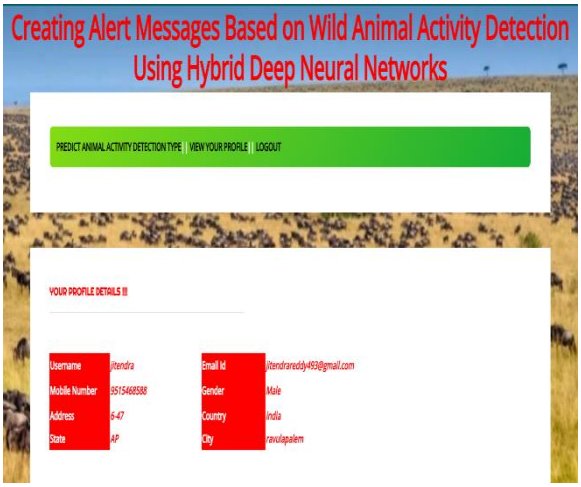

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CONCLUSION

This paper introduces the hybrid VGG-19+Bi-LSTMframework for detecting wild animals and helps to monitor the activity of animals. This hybrid approach greatly helps to save the animals from human hunting and humans from animal sudden attacks by sending an alert message to the forest officer. This model introduces novel approaches to upgrade the performance of deep learning techniques in wider applications and real time cases. The proposed model has been evaluated on four different benchmark datasets that contain animal based datasets—camera trap dataset, wild animal dataset, hoofed animal dataset, and CD net data set. The experimental results show the improved performance of our model over various quality metrics. The proposed hybrid VGG-19+Bi-LSTM model achieves above 98% average classification accuracy results and 77.2% mean Average Precision (MAP) and 170 FPS values. Henceforth, the proposed hybrid VGG-19+Bi-LSTM model out performs earlier approaches and produces greater results with lower computation time

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