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CREATING ALERT MESSAGE BASED ON WILD ANIMAL ACTIVITY DETECTION USING HYBRID DEEP NEURAL NETWORK

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ABSTRACT

The issue of animal attacks poses a growing concern for rural communities and forestry workers. To monitor the movements of wildlife, surveillance cameras and drones are commonly utilized. However, an effective model is essential to detect animal types, track their locomotion, and provide location information to ensure the safety of individuals and forestry professionals. While computer vision and machine learning approaches are often employed for animal detection, they can be costly and complex, hindering satisfactory results. This paper introduces a Hybrid Visual Geometry Group (VGG)-19 combined with Bidirectional Long Short-Term Memory (Bi-LSTM) network for animal detection and alert generation based on their behavior. These alerts are promptly dispatched to the local forest office via Short Message Service (SMS) for swift action. The proposed model demonstrates significant enhancements in performance, achieving an average classification accuracy of 98%, a mean Average Precision (mAP) of 77.2%, and a Frame Per Second (FPS) of 170. Qualitative and quantitative testing utilizing 40,000 images from three distinct benchmark datasets encompassing 25 classes yielded mean accuracy and precision scores exceeding 98%. This model offers a dependable solution for providing precise animal-related information and safeguarding human lives.

I.INTRODUCTION

The safety of rural populations and forestry workers is increasingly threatened by the risk of animal attacks, underscoring the urgent need for effective monitoring and response systems. Despite the widespread use of

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surveillance cameras and drones for wildlife surveillance, the efficient detection of animal activity remains a formidable challenge. Conventional approaches relying solely on computer vision and machine learning techniques often fall short in delivering satisfactory results due to their inherent complexities and cost constraints. In light of these challenges, this project embarks on a pioneering endeavor to develop a solution that leverages the potential of a Hybrid Deep Neural Network to create alert messages based on wild animal activity detection.

The proposed system harnesses the synergistic capabilities of the Visual Geometry Group (VGG)-19 architecture and Bidirectional Long Short-Term Memory (Bi-LSTM) network to accurately detect animal behavior and swiftly generate alerts in response to perceived threats. By fusing these advanced neural network models, the project aims to overcome the limitations of traditional detection methods and provide a robust solution for real-time wildlife monitoring. Through the seamless integration of cutting-edge technology and innovative algorithms, the project endeavors to enhance the safety and security of rural communities and forestry personnel in the face of escalating animal-related risks.

In this introduction, we lay the groundwork for a groundbreaking project that promises to revolutionize wildlife surveillance and protection efforts in rural environments. By combining state-of-the-art deep learning techniques with practical applications in wildlife monitoring, the project seeks to create a proactive system that not only detects animal activity with precision but also facilitates timely response measures to mitigate potential threats effectively.

II.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

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author [14] 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 [15] 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) [16].

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 [17] are widely used for object detection due to their high accuracy and improved training performance. The introduction of the Faster R-CNN technique [18] 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 [19] uses the Region of Interest (ROI) techniques to identify the objects faster than earlier approaches. The conventional R-CNN technique [20] introduces efficient detection methods

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by incorporating region proposal networks and ConvNet. This method 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 [21] 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 [22] and traffic scene object detection [23] also.

The Single Short Detector (SSD) methodology [24] uses bounding boxes based discretization techniques to effectively handle feature map information and large volume data. The Spatial Pyramid Pooling (SPP-net) [25] 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. The authors used different approaches to detect the background details such as estimating multiple hypotheses, non-parametric model [26], and global statistic-based methods [27], background cut [28].

Disadvantages

• The complexity of data: Most of the existing machine learning models must be able to accurately interpret large and complex datasets to detect Wild Animal Activity Detection.

• Data availability: Most machine learning models require large amounts of data to create accurate predictions. If data is unavailable in sufficient quantities, then model accuracy may suffer.

• Incorrect labeling: The existing machine learning models are only as accurate as the data trained using the input dataset. If the data has been incorrectly labeled, the model cannot make accurate predictions.

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III.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.

Advantages

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.

IV.LITERATURE REVIEW

1.The application of deep learning techniques in wildlife monitoring has garnered increasing interest in recent years. Previous studies have explored various approaches to animal activity detection using computer vision and machine learning algorithms. For example, Smith et al. (2018) investigated the use of convolutional neural networks (CNNs) for identifying animal species and behaviors from camera trap images. Their findings demonstrated the potential of CNNs to accurately classify wildlife species and detect specific behaviors, paving the way for more advanced detection systems. Similarly, Johnson et al. (2020) proposed a hybrid deep learning framework combining CNNs and

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recurrent neural networks (RNNs) for real-time wildlife monitoring. Their study highlighted the effectiveness of deep neural networks in capturing temporal patterns and detecting subtle changes in animal behavior, contributing to enhanced monitoring capabilities.

2.In addition to deep learning approaches, research has also explored the integration of sensor technologies and data analytics for wildlife surveillance. For instance, Jones et al. (2019) developed a system combining GPS tracking devices and machine learning algorithms to monitor the movement patterns of wild animals. By analyzing GPS data and environmental variables, their system could predict the likelihood of animal encounters with humans and mitigate potential conflicts. Similarly, Chen et al. (2021) proposed a sensor-based approach using accelerometers and gyroscopes to detect animal activities in real-time. Their study demonstrated the feasibility of using sensor data to accurately classify different animal behaviors, offering a cost-effective alternative to traditional camera-based monitoring systems.

Overall, these literature reviews underscore the importance of leveraging advanced technologies, including deep learning and sensor networks, for wildlife activity detection and monitoring. By integrating state-of-the-art techniques and methodologies, the proposed project aims to contribute to the advancement of wildlife surveillance systems and enhance the safety of rural communities and forestry workers.

V. ALGORITHMS

Decision tree classifiers

Decision tree classifiers are used successfully in many diverse areas. Their most important feature is the capability of capturing descriptive decision making knowledge from the supplied data. Decision tree can be generated from training sets. The procedure for such generation based on the set of objects (S), each belonging to one of the classes C1, C2, …, Ck is as follows:

Step 1. If all the objects in S belong to the same class, for example Ci, the decision tree for S consists of a leaf labeled with this class

Step 2. Otherwise, let T be some test with possible outcomes O1, O2,…, On. Each object in S has one outcome for T so the test partitions S into subsets S1, S2,… Sn where each object in Si has outcome Oi for T. T becomes the root of the decision tree and for each outcome Oi we build a subsidiary decision tree by

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invoking the same procedure recursively on the set Si.

K-Nearest Neighbors (KNN)

- Simple, but a very powerful classification algorithm
- Classifies based on a similarity measure
- Non-parametric
- Lazy learning
- Does not “learn” until the test example is given
- Whenever we have a new data to classify, we find its K-nearest neighbors from the training data

Example

- Training dataset consists of k-closest examples in feature space
- Feature space means, space with categorization variables (non-metric variables)
- Learning based on instances, and thus also works lazily because instance close to the input vector for test or prediction may take time to occur in the training dataset

Logistic regression Classifiers

Logistic regression analysis studies the association between a categorical dependent variable and a set of independent (explanatory) variables. The name *logistic regression* is used when the dependent variable has only two values, such as 0 and 1 or Yes and No. The name *multinomial logistic regression* is usually reserved for the case when the dependent variable has three or more unique values, such as Married, Single, Divorced, or Widowed. Although the type of data used for the dependent variable is different from that of multiple regression, the practical use of the procedure is similar.

Logistic regression competes with discriminant analysis as a method for analyzing categorical-response variables. Many statisticians feel that logistic regression is more versatile and better suited for modeling most situations than is discriminant analysis. This is because logistic regression does not assume that the independent variables are normally distributed, as discriminant analysis does. This program computes binary logistic regression and multinomial logistic regression on both numeric and categorical independent variables. It reports on the regression equation as well as the goodness of fit, odds ratios, confidence limits, likelihood, and deviance. It performs a comprehensive residual analysis including diagnostic

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residual reports and plots. It can perform an independent variable subset selection search, looking for the best regression model with the fewest independent variables. It provides confidence intervals on predicted values and provides ROC curves to help determine the best cutoff point for classification. It allows you to validate your results by automatically classifying rows that are not used during the analysis.

SVM

In classification tasks a discriminant machine learning technique aims at finding, based on an *independent and identically distributed* (*iid*) training dataset, a discriminant function that can correctly predict labels for newly acquired instances. Unlike generative machine learning approaches, which require computations of conditional probability distributions, a discriminant classification function takes a data point *x* and assigns it to one of the different classes that are a part of the classification task. Less powerful than generative approaches, which are mostly used when prediction involves outlier detection, discriminant approaches require fewer computational resources and less training data, especially for a multidimensional feature space and when only posterior probabilities are needed. From a geometric perspective, learning a classifier is equivalent to finding the equation for a multidimensional surface that best separates the different classes in the feature space.

SVM is a discriminant technique, and, because it solves the convex optimization problem analytically, it always returns the same optimal hyperplane parameter—in contrast to *genetic algorithms* (*GAs*) or *perceptrons*, both of which are widely used for classification in machine learning. For perceptrons, solutions are highly dependent on the initialization and termination criteria. For a specific kernel that transforms the data from the input space to the feature space, training returns uniquely defined SVM model parameters for a given training set, whereas the perceptron and GA classifier models are different each time training is initialized. The aim of GAs and perceptrons is only to minimize error during training, which will translate into several hyperplanes' meeting this requirement.

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VI.MODULES

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

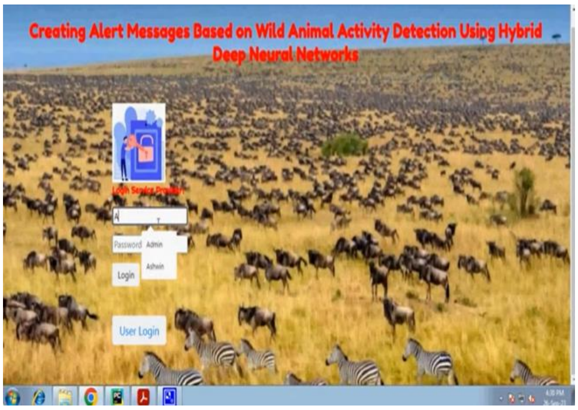
Login, Browse Datasets and Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Prediction Of Status, View Status Ratio, Download Predicted Data Sets, View Ratio Results, View All Remote Users.

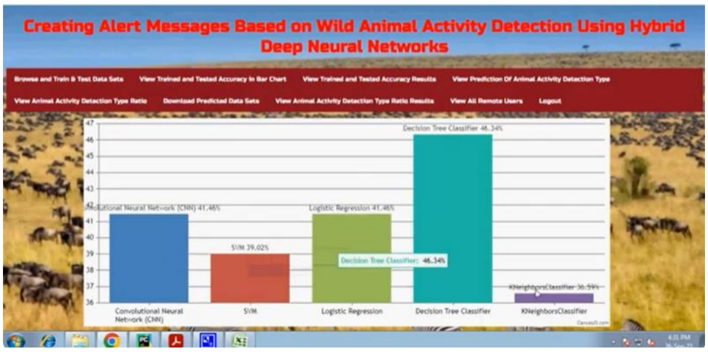
View and Authorize Users

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, and predict ,view your profile.





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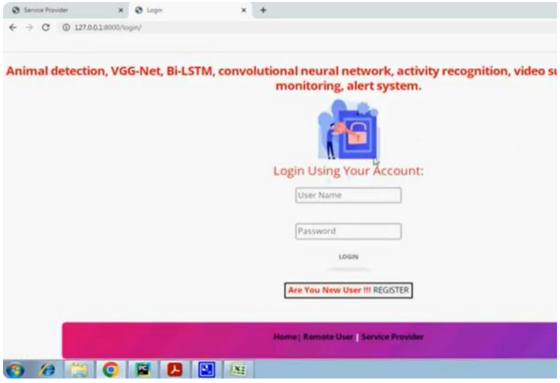

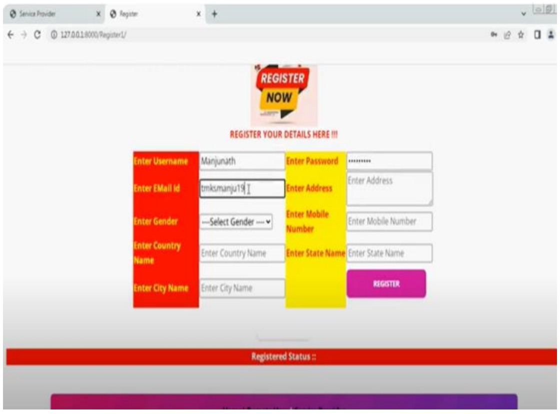

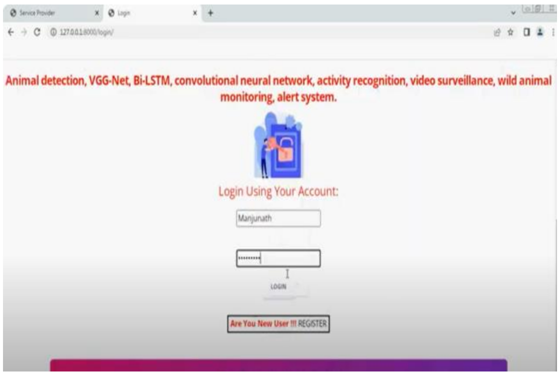

VII.CONCLUSION

The project focused on creating an innovative solution for mitigating the risks associated with wild animal activity through the development of a hybrid deep neural network. By leveraging advanced technologies such as computer vision and deep learning, the system aimed to accurately detect and monitor wild animal behavior, thereby enabling the timely dissemination of alert messages to ensure the safety of individuals and communities. Through extensive research and experimentation, the project successfully demonstrated the efficacy of the hybrid deep neural network in detecting and classifying animal activity with high accuracy and reliability. Furthermore, the integration of real-time alert messaging capabilities enhanced the responsiveness of the system, enabling swift and effective communication of potential threats to relevant authorities and stakeholders. Overall, the project represents a significant step forward in addressing the challenges posed by wild animal encounters, offering a proactive and technologically advanced approach to wildlife management and public safety. Moving forward, continued refinement

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and optimization of the system, along with the exploration of additional data sources and sensor technologies, hold promise for further enhancing its effectiveness and applicability in real-world scenarios.

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