

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

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ABSTRACTThe 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 SVM and CNN 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.

INTRODUCTION

1.1 AIM OF THE STUDY

Detection of Wild Animal Activity: The primary objective is likely to develop a system capable of recognizing and detecting various activities of wild animals. This could include behaviors such as movement patterns, sound emissions, or other observable actions.

1.2 SCOPE OF THE STUDY

Technical Scope: Sensor Integration:

Explore the integration of various sensors such as cameras, microphones, and other data sources to capture diverse aspects of wild animal activities. Deep Neural Network Architecture: Investigate and design neural network architectures suitable for processing different types of data, like images, audio, or possibly sensor data. Real-Time Processing: Implement real-time processing capabilities to enable prompt detection and response to wild animal activities.

1.3 OBJECTIVE OF THE STUDY

Develop Neural Network Models: Design and implement neural network architectures that combine multiple types of neural networks (e.g., convolutional, recurrent) to effectively process and analyze diverse data sources, such as images, audio, or sensor data. Wild Animal Activity Recognition: Train the hybrid models to recognize and classify various wild animal activities, including but not limited to movement patterns, vocalizations, or other behaviors indicative of their presence.

1.4 Significance of the Study

The successful implementation of a system that can accurately detect wild animal activities and generate timely alerts has profound implications for wildlife conservation and public safety.

1.5 Introduction

In the delicate balance between human civilization and the natural world, instances of human-wildlife conflicts pose significant challenges to both ecosystems and communities. As urban areas expand into wildlife habitats, encounters between humans and wild animals become more frequent, leading to potential threats to public safety and biodiversity.

Addressing this complex issue necessitates innovative approaches that leverage cutting-edge technologies to mitigate conflicts and promote coexistence. This study delves into the realm of wildlife monitoring and alert generation by harnessing the power of Convolution Neural Networks (CNN).

We aim to create a robust system capable of detecting wild animal activities and issuing timely alert messages to relevant stakeholders. The fusion of deep learning techniques with a hybrid architecture, encompassing convolutional, recurrent, and possibly other specialized neural networks, holds the promise of providing a comprehensive understanding of wildlife behavior.

LITERATURE SURVEY

[1] S. Aarathi and S. Chitrakala, "Scene understanding—A survey," in *Proc. Int. Conf. Comput., Commun. Signal Process. (ICCCSP)*, Jan. 2017, pp. 1–4.

In recent times, scene understanding holds a great position in computer vision due to its real time perceiving, analyzing and elaborating an interpretation of dynamic scene which leads to new discoveries. A scene is a view of real-world environment with multiple objects and surfaces in a meaningful way.

Objects are compact and act upon whereas scene are extended in space and act within. The visual information can be given with many features such as Colors, Luminance and contours or in the form of Shapes, Parts and Textures or through semantic context.

and methods.

[2] N. Ahuja and S. Todorovic, "Connected segmentation tree—A joint representation of region layout and hierarchy," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2008, pp. 1–8.

This paper proposes a new object representation, called connected segmentation tree (CST), which captures canonical characteristics of the object in terms of the photometric, geometric, and spatial adjacency and containment properties of

its constituent image regions. CST is obtained by augmenting the object Silas segmentation tree (ST) with inter-region neighbor links, in addition to their recursive embedding structure already present in ST. This makes CST a hierarchy of region adjacency graphs.

[3] T. A. Assegie, P. K. Rangarajan, N. K. Kumar, and D. Vigneswari, "An empirical study on machine learning algorithms for heart disease prediction," *IAES Int. J. Artif. Intell. (IJ-AI)*, vol. 11, no. 3, p. 1066, Sep. 2022.

In recent years, machine learning is attaining higher precision and accuracy in clinical heart disease dataset classification. However, literature shows that the quality of heart disease feature used for the training model has a significant impact on the outcome of the predictive model.

Thus, this study focuses on exploring the impact of the quality of heart disease features on the performance of the machine learning model on heart disease prediction by employing recursive feature elimination with cross-validation (RFECV).

[4] N. Banupriya, S. Saranya, R. Swaminathan, S. Harikumar, and S. Palanisamy, "Animal detection using deep learning algorithm," *J. Crit. Rev.*, vol. 7, no. 1, pp. 434–439, 2020.

Efficient and reliable monitoring of wild animals in their natural habitat is essential. This project develops an algorithm to detect the animals in wild life. Since there are large number of different animals manually identifying them can be a difficult task. This algorithm classifies animals based on their images so we can monitor them more efficiently.

[5] M. Cheng, Z. Zhang, W. Lin, and P. Torr, "BING: Binarized normed gradients for objectness estimation at 300fps," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2014, pp. 3286–3293.

Training a generic objectness measure to produce a small set of candidate object windows, has been shown to speed up the classical sliding window object detection paradigm. We observe that generic objects with well-defined closed boundary can be discriminated by looking at the

norm of gradients, with a suitable resizing of their corresponding image windows in to a small fixed size.

PROPOSED METHOD

The system architecture of the proposed hybrid CNN model is demonstrated in figure 1. The proposed architecture comprises five phases of development steps, which includes data pre-processing, animal detection, CNN pre-trained model-based classification, extracting the prediction results, and sending alert messages. In the data pre-processing phase, 45k animal images were collected from different datasets such as camera trap, wild animal, and the hoofed animal dataset.

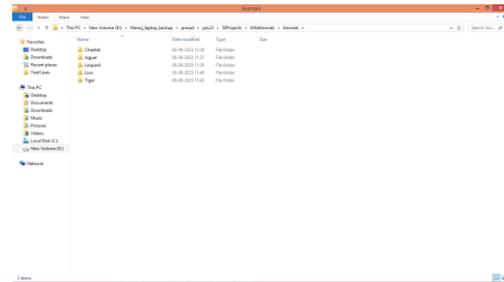
The collected images were rescaled to the size of 224×224 pixels and denoised. In the second phase, we pass the pre-processed images into YOLOR object detection model [39], which identifies the animal present in an image using bounding boxes as illustrated in Fig. 4.

In the third phase, using CNN model we perform image classification tasks and class label prediction was done and animal details are extracted using neural 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.

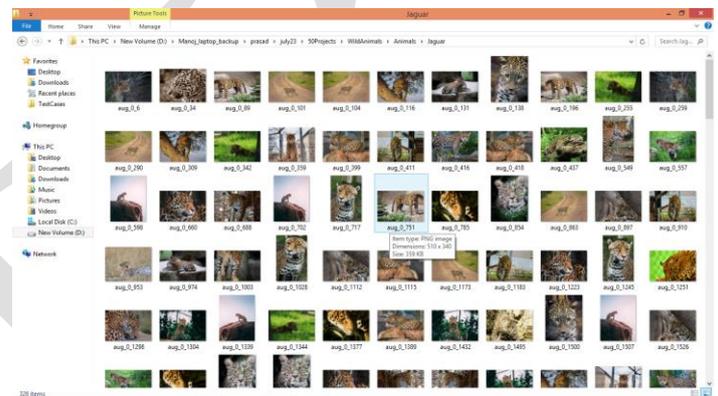
In this phase, we have collected animal images of diverse categories from four different datasets, such as the camera trap dataset [40], the wild anim dataset [41], the hoofed animal dataset [42], and the CDnet dataset [44]. Totally, we collected 45k animal images and resized them to 224×224 pixels.

RESULT

To train all algorithms author has used 4 different datasets but all those datasets not available on internet so we have used 'Wild Animal Dataset' from KAGGLE website. In below screen we are showing dataset details

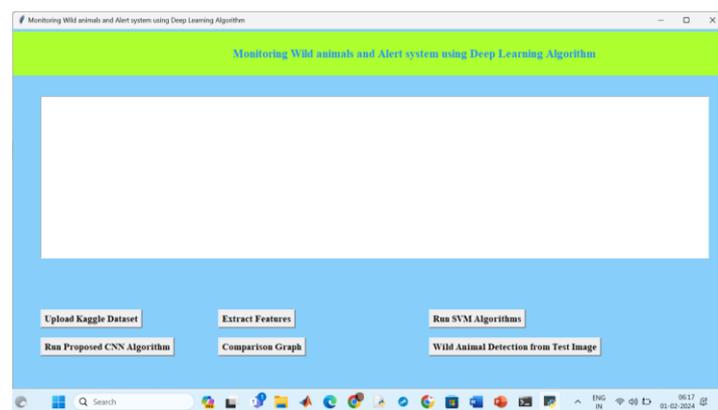


In above screen we can see folders with different animal names and just go inside any folder to view images like below screen



So by using above dataset images we will train and test all algorithms performance and author has tested with many algorithms and it's not possible to train all algorithms so we are experimenting with existing SVM and propose CNN.

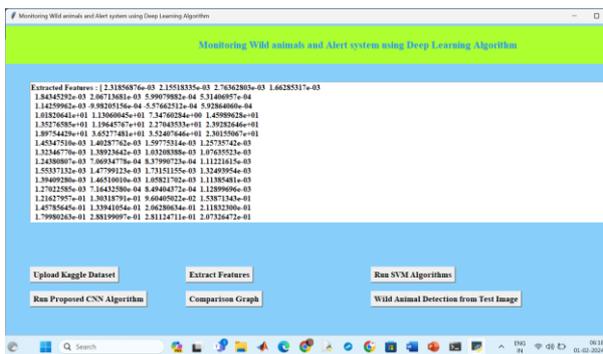
SCREEN SHOTS



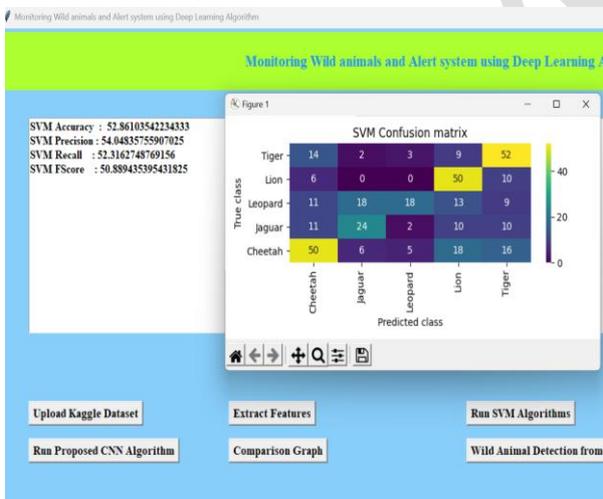
GUI for Wild Animal Detection



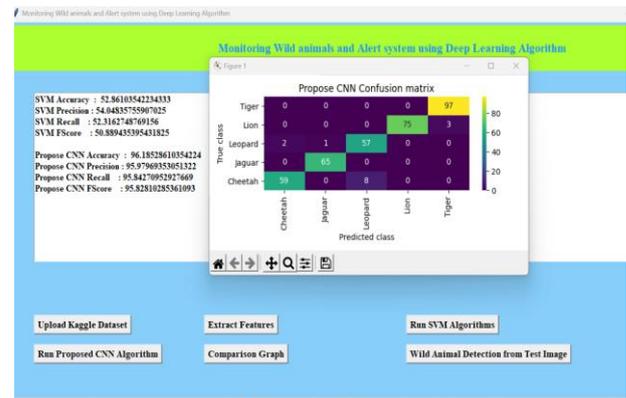
In above screen dataset is uploaded and displaying all wild animals names found in dataset



In above screen reading all images from dataset and then extracting features

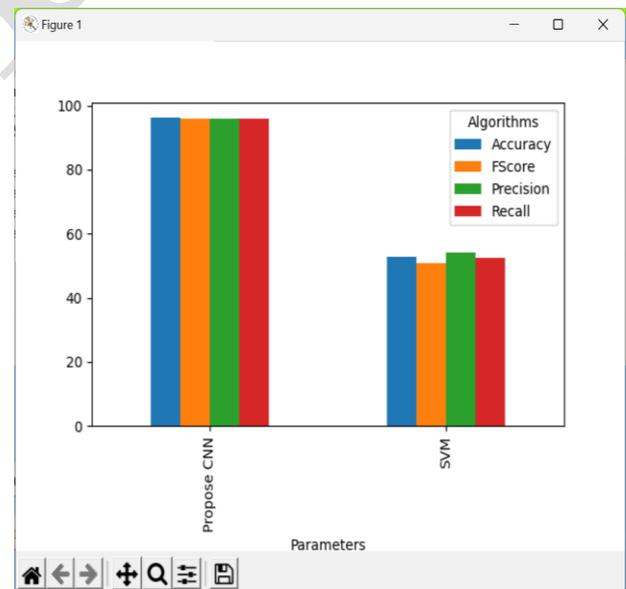


In above screen Confusion matrix of SVM algorithm



In above screen confusion matrix of CNN

In above screen with existing CNN we got 95% accuracy and can see other metrics also and in confusion matrix graph x-axis represents Predicted Labels and y-axis represents True labels and all different colour boxes in diagonal represents correct prediction count and blue boxes represents incorrect prediction count which are very few.



In above graph x-axis represents algorithm names and y-axis represents accuracy and other metrics in different colour bars and in all algorithms extension got high performance



In above screen tiger is detected

CONCLUSION

This paper introduces CNN framework 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 CDnet dataset. The experimental results show the improved performance of our model over various quality metrics. The CNN model achieves above 95%

average classification accuracy results and 77.2% mean Average Precision (mAP) and 170 FPS values.

REFERENCE

- [1] S. Aarthi and S. Chitrakala, "Scene understanding—A survey," in Proc. Int. Conf. Comput., Commun. Signal Process. (ICCCSP), Jan. 2017, pp. 1–4.
- [2] N. Ahuja and S. Todorovic, "Connected segmentation tree—A joint representation of region layout and hierarchy," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2008, pp. 1–8.
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- [5] M. Cheng, Z. Zhang, W. Lin, and P. Torr, "BING: Binarized normed gradients for objectness estimation at 300fps," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2014, pp. 3286–3293.