



# Wildlife Detection and Intrusion Alert System

Arun Yogesh M<sup>1</sup>, Harivishwesh K<sup>2</sup>, Ishan Gupta<sup>3</sup>, Maheswari M<sup>4</sup>

Student, Computer science and engineering, Anand Institute of Higher Technology, Chennai, India<sup>1</sup>

Student, Computer science and engineering, Anand Institute of Higher Technology, Chennai, India<sup>2</sup>

Student, Computer science and engineering, Anand Institute of Higher Technology, Chennai, India<sup>3</sup>

Assistant Professor, Computer Science and Engineering, Anand Institute of Higher Technology, Chennai, India<sup>4</sup>

**Abstract:** Wild animal intrusion has always been a persisting problem. A lethal conflict is below way among India's developing population and its wildlife limited to ever-shrinking forests and grasslands. In forest and agricultural zones, human animal conflict is quite an issue where enormous amounts of resources are lost and human life is threatened. The reason behind animals attacking humans cannot be confined to a single cause. Certain animal attacks happen due to humans provoking them and others are purely based on instinct which is often the case and for which nothing can be done. There are no specific reasons for animals attacking humans based on instincts. In any way, animal attacks are daunting.

Apart from posing a threat to human life, Crop damage caused by animal attacks resulting in reducing the crop yield is also yet another consequence. Hence their activity must be monitored continuously in order to take action in case of animal intrusion in attack prone areas. Due to the diverse nature of movement and physical sizes of wild animals, it is a challenging task to track these animals or perform surveillance. In order to tackle the issue, we are developing a system to monitor these areas that will detect the intrusion of wild animals using image processing where classification is performed using Deep learning algorithms. Suitable action is taken based on the type of intruder and an alert is sent if the type matches the predefined wild animal datasets.

**Keywords:** Intrusion alert, Faster Regional Convolutional Neural Networks, Attack prone areas, Wildlife Datasets, Deep learning

## I. INTRODUCTION

Over the years many human lives and enormous amounts of resources have been lost due to wild animal attacks. In recent times these kinds of conflicts are rising tremendously posing a major threat to human lives. So, these attack prone zones should be monitored continuously to prevent intrusion of wild animals that could cause harm. Human-animal conflicts arise due to increasing encroachment and poaching.

Humans move into the forest zone areas for the sake of livelihood, for agricultural practises and rapid industrialization which forces animals to enter nearby villages. Detecting wild animals not only protects and safeguards the local community, but also helps in accounting and keeping track of them. Animal Detection System, like our proposed model, also helps in preventing evading deaths, injuries and property damage. Though attacks cannot be totally prevented, it can be minimised and faster actions can be taken.

## II. RELATED WORKS

The proposed system for wildlife monitoring presented in [1] integrates wireless sensor networks (WISNs) with high-efficiency progressive transmission and automatic recognition of images. The use of deep convolutional neural networks (CNNs) for image super-resolution, as demonstrated in [2], can enhance the quality of the images captured by WISNs, making them more suitable for recognition tasks. Chen et al. [3] have also used deep CNNs for species recognition in wild animal monitoring, while Swann et al. [4] have evaluated the use of infrared-triggered cameras for detecting wildlife.

Other related works have explored the use of deep learning techniques for wild animal intrusion detection, such as [5] and [12], as well as the integration of IoT with animal intrusion detection systems, as shown in [6], [7], and [13]. Andavarapu et al. [8] have proposed a method for wild-animal recognition using the weighted combination of histogram of oriented gradients (W-COHOG) for agro-security, while Xue et al. [10] have proposed a system based on CNN for animal intrusion detection. Additionally, the human-wildlife conflict and management strategies have been discussed in [11], and the impact of wild animal intrusion on rural communities has been analyzed in [14].



### III. EXISTING SYSTEM

The convolutional encoder-decoder network is used to monitor wildlife images. Faster RCNN algorithm is proposed for the automatic recognition of wildlife images to improve efficiency and recognition accuracy thus overcoming the drawbacks of traditional WISNs. Machine learning concepts are used to detect animals and are especially designed for farm areas by using deep neural networks-ANN. Additional Convolutional layer is added with Convo 2D and MaxPooling is performed to increase the efficiency of the model [5]. The farm is monitored at regular intervals using cameras to detect an intrusion. GSM is used to send the alert message and appropriate sounds are played in order to drive the animal away.

### IV. PROPOSED SYSTEM

Video is captured 24/7 using surveillance cameras from which the frames are extracted. The extracted frames are fed into the computer vision model to perform segmentation by which multiple objects are extracted. The extracted objects are pre-processed and fed into a convolutional neural network where the object is identified and then classified as wild animal. Alert mail is sent to the forest official and buzzer alarm is ringed in case the detected animal is classified as Wild animal

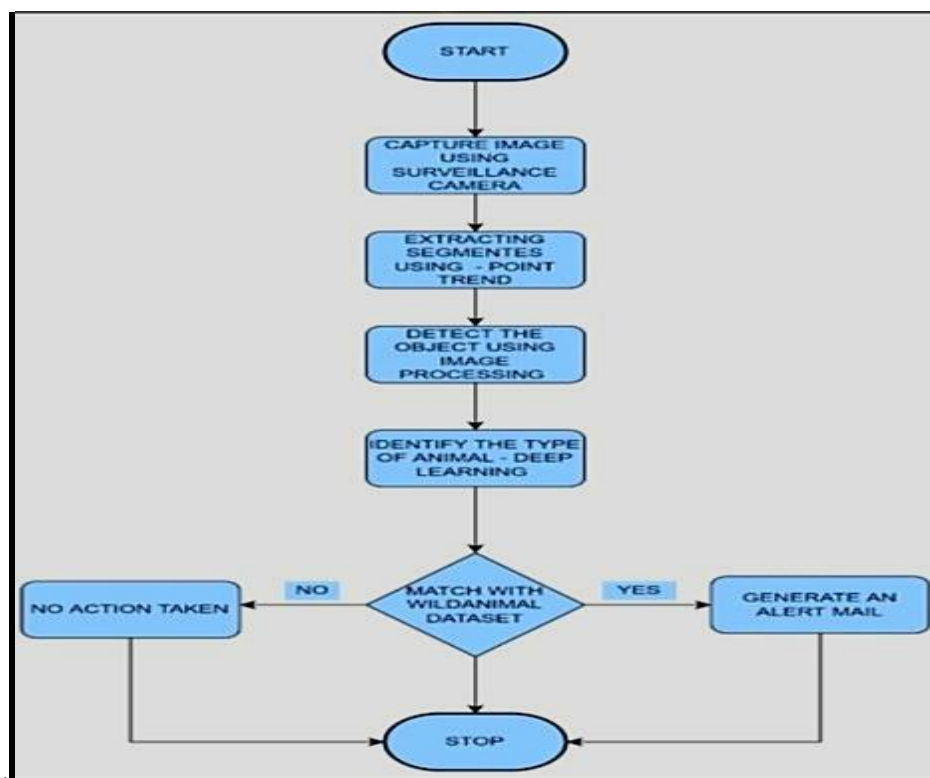


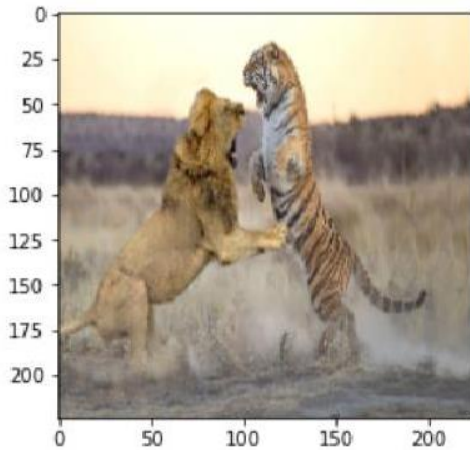
Fig. 1 System Architecture Diagram

### V. IMPLEMENTATION

To begin the process, the input test image must be obtained and preprocessed prior to its conversion into an array format, which will enable it to be compared to other images. In addition, the chosen database must also undergo proper separation and preprocessing before it can be renamed and sorted into the appropriate folders. Once the database has been correctly organized, the model must be trained using a convolutional neural network (CNN) to ensure accurate classification. This involves processing the images in the database through the CNN to identify common features and patterns that can be used to identify the target object or animal. After the model has been successfully trained, a comparison is made between the input test image and the trained model, and the results are displayed accordingly. If the image being tested contains a wild animal, the software will send an alert via SMTP to nearby officials, notifying them of the potential threat. This allows for swift action to be taken to ensure the safety of those in the surrounding area.



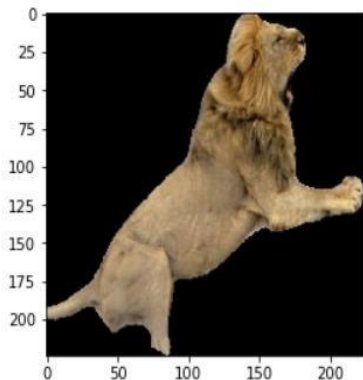
Wild animal Alert!!!  
lion 56.81%  
tiger 17.20%



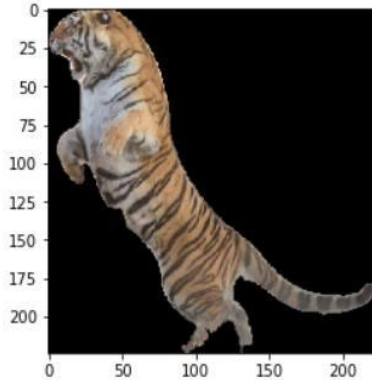
Wild animal Alert!!!  
jaguar 44.90%  
leopard 5.37%



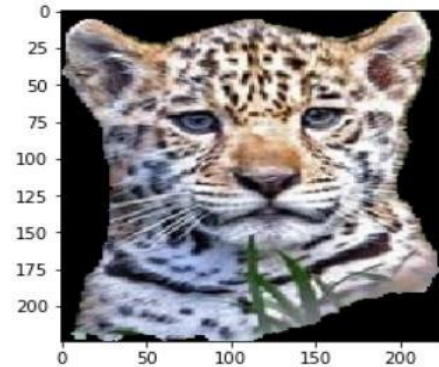
Wild animal Alert!!!  
lion 67.32%



Wild animal Alert!!!  
tiger 60.26%



Wild animal Alert!!!  
leopard 51.98%



Wild animal Alert!!!  
jaguar 61.02%

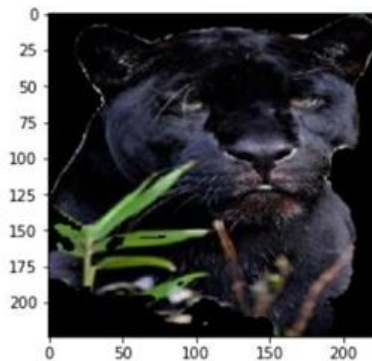


Fig. 1 Segmented Images

A. Deep Learning

Deep learning is a subset of machine learning that involves training neural networks to learn from data. It is called "deep" because these neural networks are composed of many layers, allowing them to learn increasingly complex representations of the input data. Unlike traditional machine learning algorithms, deep learning models can automatically learn features from the data, which makes them highly effective for tasks such as image recognition, speech recognition, and natural



language processing. Deep learning has made significant advancements in recent years, with applications ranging from self-driving cars to medical diagnosis. Despite its successes, deep learning remains an active area of research, with ongoing efforts to improve its scalability, interpretability, and robustness.

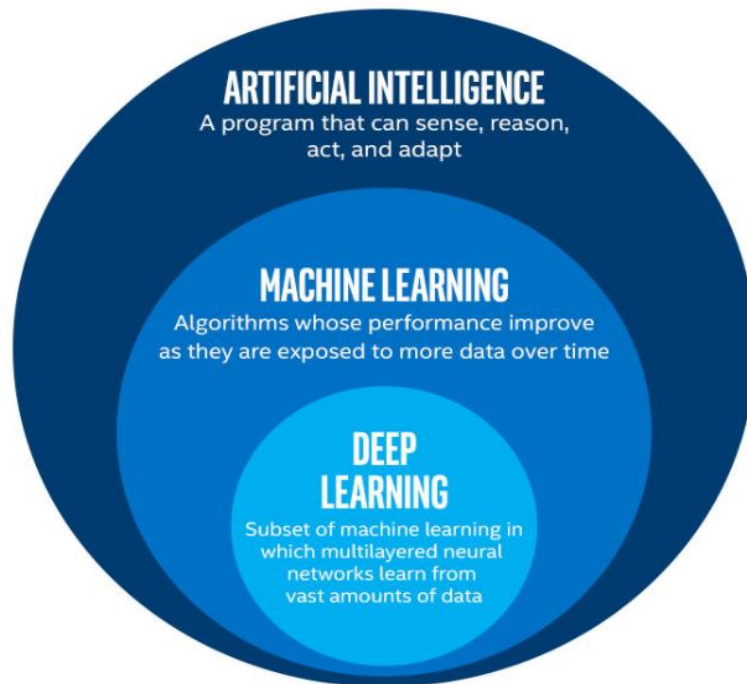


Fig. 2 Classification of Algorithm

B. Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a specialized form of neural networks that are designed to process grid-like data, such as images and videos. CNNs leverage a technique called convolution, which involves applying a set of learnable filters to the input data to extract features at different levels of abstraction. These features are then passed through a series of layers that perform operations such as pooling and activation to reduce their dimensionality and increase their representational power. The architecture of a CNN typically consists of several convolutional layers followed by a few fully connected layers that map the learned features to the output labels. CNNs have become the go-to method for image classification, object detection, and semantic segmentation, and have achieved state-of-the-art performance in these tasks. The success of CNNs can be attributed to their ability to learn hierarchical representations of the input data, which captures the important visual cues required for accurate prediction.

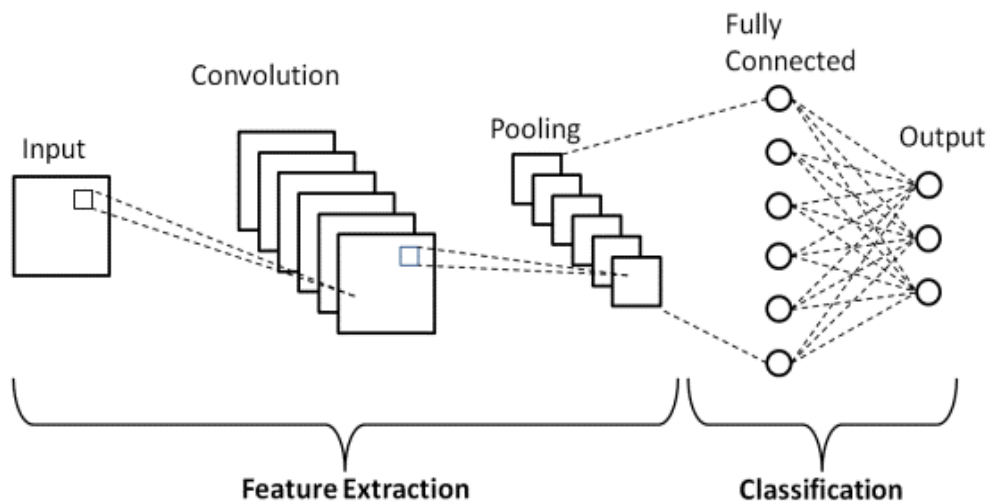


Fig. 3 CNN





### C. Dataset

The dataset in this module includes various steps involved in processing an image or video using computer vision techniques. The first step is frame extraction, which involves capturing frames from a video using OpenCV and storing them in a document. The second step is image segmentation, which is performed using PyTorch and the Pointrend model to segment individual objects in the frames. Preprocessing follows, which involves converting the segmented image into a numpy array and then expanding its dimensions. This is necessary to feed it into the model for object detection, which is done using TensorFlow and the MobileNet\_V2 convolutional neural network. The final step is SMTP, which is used to send an alert message along with the detected image to a specified email address. This is done by importing necessary packages like smtplib, MIMEText, and MIMEImage, and then connecting to the SMTP server with port 587. The dataset provides a comprehensive guide on how to implement these steps and perform object detection on a video feed.

### D. Image Preprocessing and Labelling

Image preprocessing and labeling are crucial steps in preparing data for object detection models. Image preprocessing involves a series of techniques to clean, normalize, and enhance the image data to improve the accuracy of the model. This can include steps such as resizing, cropping, and color normalization. Additionally, labeling is the process of manually identifying and marking objects of interest in the image data. Accurate labeling helps to train the object detection model to recognize and classify wildlife and other objects with high precision. Proper image preprocessing and labeling can significantly improve the effectiveness of the object detection model in identifying and alerting to potential intrusions or wildlife activity.

### E. Image Segmentation

Certainly, here are the five fundamental steps involved in segmenting a digital image for background removal:

1. **Grayscale Conversion:** The first step involves converting the colored image into a grayscale image, as it simplifies the processing by eliminating color data and reducing the image to a single channel.
2. **Thresholding:** Once the image is in grayscale, thresholding is applied to separate the foreground from the background. Thresholding is a process of setting a specific intensity value as a threshold, and pixels with intensity values above or below that threshold are assigned as either foreground or background pixels.
3. **Contour Identification:** After thresholding, the edges or contours of the foreground object are identified. Contours are simply the boundaries of objects in an image, and are useful in identifying the foreground object's shape and size.
4. **Mask Creation:** Once the contours are identified, the largest contour is used to create a binary mask that covers the entire foreground object. The mask contains only the pixel values that belong to the object, while everything else is set to 0.
5. **Background Removal:** Finally, the binary mask is applied to the original image to remove the background and isolate the foreground object. The object can then be further analyzed or processed as necessary, with the confidence that the background has been effectively removed.

### F. Data Training and Testing

Data training and testing are two essential aspects of machine learning. In data training, a model is fed labeled data to teach it how to identify patterns and relationships through various algorithms and techniques. The training process continues until the model reaches a level of accuracy that is considered satisfactory. After training, the model is then tested using a separate set of data that was not part of the training process. This testing data is used to evaluate the model's performance and accuracy, determining if the model requires further fine-tuning. Performance evaluation metrics such as precision, recall, and F1 score are often used to evaluate the testing data. It is crucial to have high-quality data for both the training and testing phases to ensure that the model can accurately generalize to new and unseen data. With a well-trained and accurately tested model, machine learning can provide valuable insights and predictions.

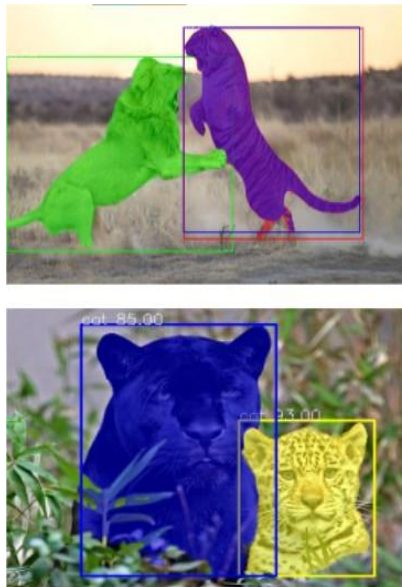
### G. Detection

Object detection is an essential computer vision task that involves identifying and localizing objects within images or videos. It aims to detect and recognize different types of real-world objects such as cars, faces, flowers, etc., in real-time with high accuracy. This method of detecting objects involves using learning algorithms and derived features to recognize all instances of an object category in an image. To achieve this, the process involves receiving an image as input, dividing it into multiple regions, treating each region as a distinct image, and sending them to a Convolutional Neural Network (CNN) to classify them. By analyzing these regions, the CNN can identify the presence of the object of interest in the image with high precision, allowing for effective object detection and recognition.



VI. RESULTS AND DISCUSSION

THE UPGRADED MODEL WITH IMAGE SEGMENTATION PERFORMS MULTIPLE OBJECT DETECTION OVERCOMING THE ISSUE OF THE EXISTING MODEL WHICH WORKS EFFECTIVELY ONLY IN THE CASES OF SINGLE OBJECT DETECTION. FLEXIBILITY TO IDENTIFY ALL THE OBJECTS AND DETECTION PERCENTAGE ARE IMPROVED SIGNIFICANTLY.



Animal	Existing model	Our Model
Tiger	17.20%	60.26%
Lion	56.81%	67.32%
Jaguar	44.90%	61.02%
Leopard	5.37%	51.98%

FIG. 4 RESULTS TABULATION

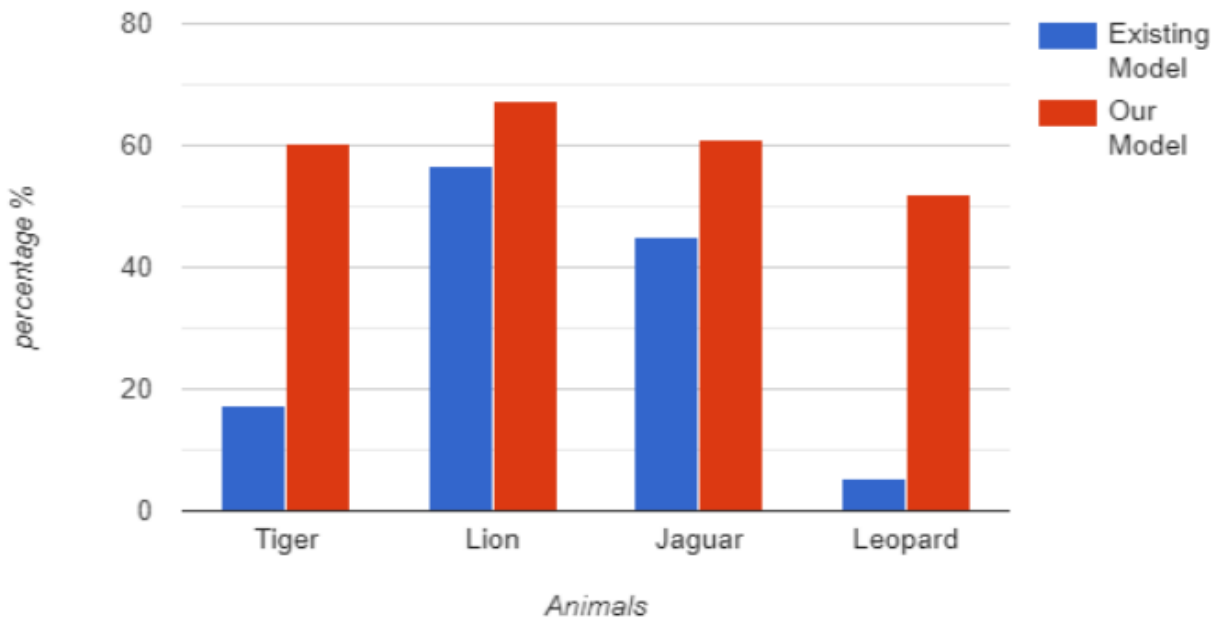
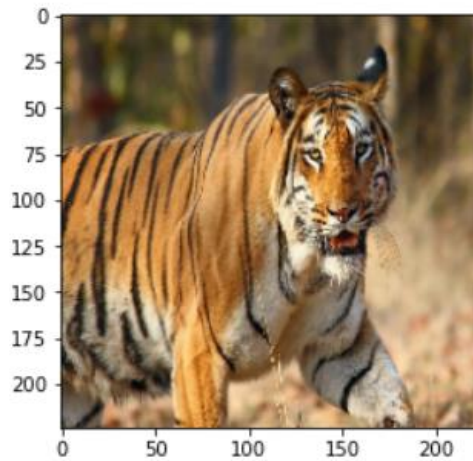


FIG. 5 PREDICTION GRAPH

## DISPLAYING IMAGE

```
In [63]: 1 import matplotlib.pyplot as plt
         2 plt.imshow(cv2.cvtColor(imgg,cv2.COLOR_BGR2RGB))
```

```
Out[63]: <matplotlib.image.AxesImage at 0x120f2cb2eb0>
```



```
In [79]: 1 resized_img= image.img_to_array(imgg)
         2 final_image= np.expand_dims(resized_img,axis=0)
         3 final_image=tf.keras.applications.mobilenet.preprocess_input(final_image)
         4 final_image.shape
```

```
Out[79]: (1, 224, 224, 3)
```

## CLASSIFICATION

```
In [67]: 1 from tensorflow.keras.applications import imagenet_utils
         2 predictions=mobile.predict(final_image)
```

```
In [68]: 1 results= imagenet_utils.decode_predictions(predictions)
```

## SUCCESSFUL DETECTION

```
In [80]: 1 a=results[0][0][1]
         2 b=results[0][0][2]*100
```

```
In [81]: 1 print(a,"{:.2f}%".format(b))
```

```
tiger 91.28%
```

Fig. 6 Detection of Single Wild Animal



```

50 cam=cv2.VideoCapture("video.mp4")
51 namedWindow("camera")
52 while True:
53     if(flag==1):
54         break
55     ret, frame = cam.read()
56     if not ret:
57         break
58     cv2.imshow("camera",frame)
59     cv2.imwrite('./animals/'+str(count)+'.jpg', frame)
60     detection()
61
62     if cv2.waitKey(10)==27:
63         break
64     count=count+1
65
66 cam.release()
67 cv2.destroyAllWindows()
68

```

```

cheetah 61.08%
Wild animal alert!!!
cheetah 59.78%
cheetah 58.10%
cheetah 63.45%
Wild animal alert!!!

```

```

cheetah 37.41%
cheetah 37.60%
cheetah 33.51%
cheetah 35.12%
leopard 26.27%
leopard 25.95%
leopard 31.09%
cheetah 39.64%
cheetah 44.75%
leopard 36.24%
leopard 34.11%
cheetah 43.72%
cheetah 45.33%
cheetah 52.68%
cheetah 53.82%
cheetah 53.40%
cheetah 55.54%
cheetah 49.02%
cheetah 50.30%
cheetah 51.79%
cheetah 49.85%
cheetah 41.14%

```

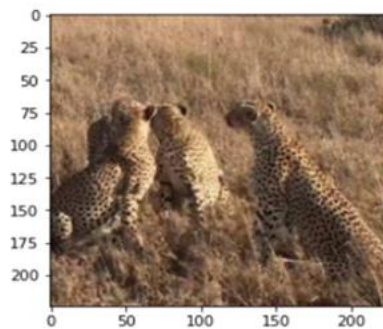


Fig. 7 Detection of multiple Wild Animal





## VII. CONCLUSION

Human-animal conflicts are a growing concern across the world, with incidents occurring almost every other day. These conflicts pose a serious threat to the lives of thousands of people, as well as to the well-being of animals and the environment. In order to mitigate these conflicts, there is a need for effective and efficient systems that can detect and prevent them from happening. One such system is the wildlife detection and alert system, which can help eliminate human and animal deaths and injuries, and also prevent damage to crops, properties and even lives of other animals. This system can also aid forest departments and other responsible authorities in monitoring animal movement, thus preventing them from straying out of their habitation zones.

The proposed system uses advanced technology to detect and classify wild animals in real-time. When an animal is detected, the system immediately sends an alert mail to forest officials and sounds a buzzer alarm to alert the locals. This timely response helps in preventing human-animal conflicts and safeguarding lives and property. Furthermore, this system is also capable of preventing crop damage caused by animal intrusion, thus helping farmers protect their crops and livelihoods. By providing an early warning system, the proposed technology can help mitigate the risks associated with human-animal conflicts, and ensure the safety of both humans and animals. In conclusion, the wildlife detection and alert system proposed in this context provides an effective and efficient solution to human-animal conflicts. The technology helps in preventing loss of life, property, and crop damage by detecting and alerting the concerned authorities in real-time. It is an important step towards ensuring the safety of both humans and animals, and towards creating a harmonious coexistence between them.

## REFERENCES

- [1]. Wenzhao Feng, Anqi Li, Junguo Zhang, Weidong Bao, "High-Efficiency Progressive Transmission and Automatic Recognition of Wildlife Monitoring Images With WISNs" IEEE Access, vol 9, November 2019
- [2]. C. Dong, C. C. Loy, K. He, and X. Tang, "Image super-resolution using deep convolutional networks," IEEE Trans. Pattern Anal. Mach. Intell., vol. 38, no. 2, pp. 295–307, Feb. 2016
- [3]. G. Chen, T. Han, Z. He, R. Kays, and T. Forrester, "Deep convolutional neural network-based species recognition for wild animal monitoring," in Proc. IEEE Conf. Image Process., Oct. 2015, pp. 858–862.
- [4]. D. E. Swann, C. C. Hass, D. C. Dalton, and S.A. Wolf, "Infrared-triggered cameras for detecting wildlife: An evaluation and review," Wildlife Soc. B., vol. 32, no. 2, pp. 357–365, Jun. 2004.
- [5]. DR.R.S. Sabeenian, N. Deivanai, and B. Mythili "Wild Animals Intrusion Detection using Deep Learning Technique": International Journal of Pharmaceutical Research, Vol 12, Oct 2020
- [6]. Prajna P, Soujanya B S and Mrs Divya "IoT-based Wild Animal Intrusion Detection System" in Proc. ICRTT Conference, Jun. 2018
- [7]. Dr.P.Uma Maheshwari and Anjali Rose Rajan "Animal Intrusion Detection System Using Wireless Sensor Networks," International Journal of Advanced Research, Vol. 2, Mar 2016.
- [8]. Andavarapu, Nagaraju, and Valli Kumari Vatsavayi. "Wild-animal recognition in agriculture farms using W-COHOG for agro-security." International Journal of Computational Intelligence Research 13, no. 9 (2017): 2247-2257.
- [9]. Santhiya, S., Y. Dhamodharan, N. E. Kavi Priya, C. S. Santhosh, and M. Surekha. "A smart farmland using Raspberry Pi crop prevention and animal intrusion detection system." Int. Res. J. Eng. Technol (2018).
- [10]. Xue, Wenling, Ting Jiang, and Jiong Shi. "Animal intrusion detection based on convolutional neural network." In 2017 17th International Symposium on Communications and Information Technologies (ISCIT), pp. 1-5.
- [11]. Distefano, Elisa. "Human-Wildlife Conflict worldwide: collection of case studies, analysis of management strategies and good practices." Food and Agricultural Organisation of the United Nations (FAO), Sustainable Agriculture and Rural Development Initiative (SARDI), Rome, Italy. (2005).
- [12]. Yin, Chuanlong, Yuefei Zhu, Jinlong Fei, and Xinzhen He. "A deep learning approach for intrusion detection using recurrent neural networks." Ieee Access 5 (2017): 21954-21961
- [13]. Muneera Begum H, Janeera.D.A and Aneesh Kumar.A.G, "Internet of Things based Wild Animal Infringement Identification, Diversion and Alert System" in Proc. IEEE Conf. Inventive Computation Technologies (ICICT-) IEEE Xplore, jun. 2020
- [14]. Arunashantha, H. A. S. "Wild animal intrusion on the rural community with special references to north western slope of Sinharaja Forest Reserve." (2015).