Loganathan N / Afr.J.Bio.Sc. 6(5) (2024). 4643-4656 ISSN: 2663-2187

https://doi.org/ 10.33472/AFJBS.6.5.2024. 4643-4656

African Journal of Biological Sciences

DEVELOPMENT OF A PENETRATION MONITORING AND REPELLENT METHOD FOR WILD ANIMALS USING YOLOV3, OPENCV, AND PYTHON

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Article History
Volume 6, Issue 5, 2024
Received: 09 May 2024
Accepted: 17 May 2024
doi: *10.33472/AFJBS.6.5.2024. 4643-4656*

ABSTRACT

In India, there has been a notable struggle between the population growth and the wildlife. Injuries, fatalities, destruction of human habitation, crop devastation, and human property damage are only a few of the serious effects. Temporary measures to safeguard the habitat, such as electric fences, trenches, manual surveillance, guard dogs, etc., are used, but they are not cost-effective and have beenshown to be harmful for both humans and wildlife. Some sort of mitigation strategy is needed to address this problem in a way that ensures the safety of both wild animals and people. Inspite of manyresults to monitor animal safety, AI provides additional benefits. An obstacle which revolve around this problem may undoubtedly be pushed forward by using IoT alone. Development of new methodology to identify the incursion of forest creatures after which they need to be sent again to their place safely can be obtained using the introduced idea. Also, this idea helps in human safety against animal attack on them. In the proposed work, we combine YOLOv3 weights and machine learning approaches to address the issue at hand by reducing the time it takes to recognize many objects while maintaining the highest level of time complexity. The pre-defined neural network algorithm referred to as the YOLO framework will be used to process the captured image. When an object is recognized, the processor sends an email updating the presence of animals, and a buzzer turns on when Arduino is activated, simultaneously turning on the speaker with crackers sounds to repel animals. Through the IOT module, it sends the taken photographs to the mail of the authorizedperson.

Keywords: YOLOv3 weights, machine learning, neural network, Arduino

1. Introduction

Farming has long been the most significant industry in India. Wild creatures are increasingly forced to live alongside populated areas and target cows and other such beings that includes humans as well because of territory deterioration, destroying trees, and shortage of food. Because of this, animals have started attacking humans in search of food. Elephant intrusion is a more intense form of conflict than other tigers, and it is to blame for the deaths of people. As a result of competition between humans and animals and population growth, humans began destroying forests to survive, which harmed animals and their habitats. Due to the increased industrialization of forested areas, animals began approaching surrounding villages. They become hysterical and pretend to attack crops, livestock, sometimes people, and farming grounds when they lose their means of subsistence and the dryness.

While numerous studies have been conducted to identify crop damage issues and avoid animal intrusion, only a few of them have focused on the methods and efficacy of practices used to minimize wildlife damage (P. Prajna et.al 2018).

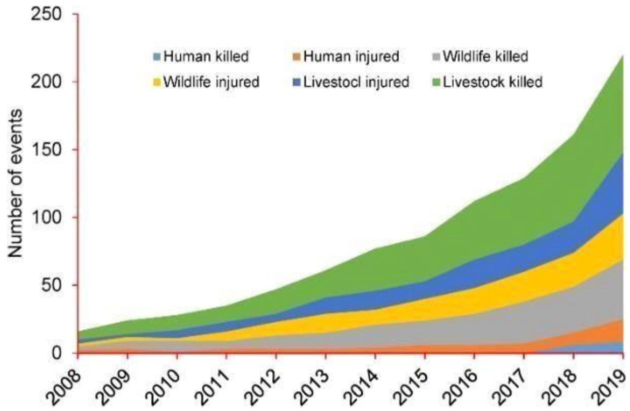

Figure 1. Percentage of Animal Assaults on People and Livestock as well as the Percentage of Wildlife Killed by Humans

The statistical data between the animal assaults on people, livestock and the percentage of wildlife killed by humans is depicted in figure 1.

2. Problem Statement

Conflicts between humans and wildlife have led to a number of significant changes in agricultural patterns and practices across the country. In areas where the fencing is unsuccessful, farmers decide to stay up all night to protect their crops from animal intrusions as shown in figure 2. Farmers have begun installing electric fences around their fields to prevent crop loss caused by animal invasions as shown in figure 3.

Figure 2. Animal Upsetting the Planted Crops and Picture of Electric Fencing

In some extreme cases, these kinds of practices have even led to the loss in humans and animals count. The solution to this problem is the intellectual observing unit to detect habitually, recognize the picture of the creature incoming and transmit a human alert message.

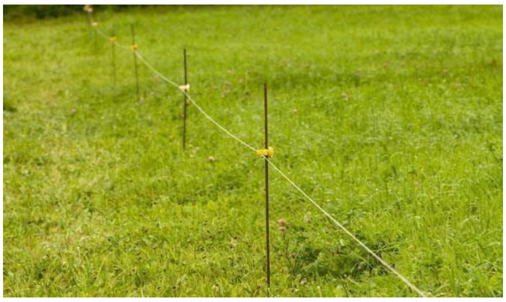

Figure 3. Electrical Fencing

This work aims at implementing repellant systems in wildlife conservation areas to prevent animals from escaping, and it makes use of IR cameras to find animals at night.

2.1. Object Detection Based on Deep Learning

Among the disciplines of PC domain, deep learning, AI, object detection founds to be a fundamental research area. Further, the difficult PC visual tasks like aim chasing, occasion finding, performance investigation also scenario pictorial identification, this serves as a vital precursor. It seeks to accurately identify the category, pinpoint at aim to focus inside a picture, and provide a bounding case of each target as shown in figure 4. It is frequently utilized in areas such as intellectual filmed observation, therapeutic picture study, automatic driving of vehicles, industrial inspection video and picture retrieval.

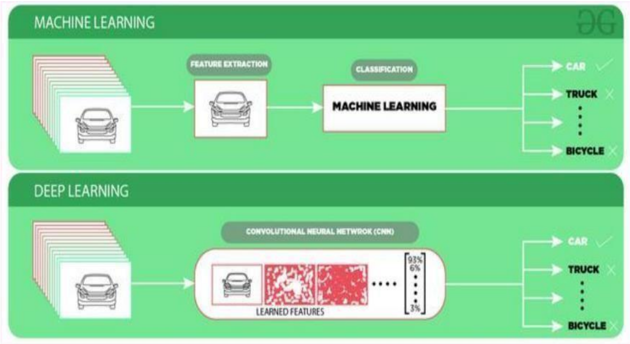

Figure 4. Object Detection using ML and DL

Traditional detection techniques on manually extracting features contain major steps and drawbacks. One of the most often used techniques to recognize the picture is the convolution neural network (CNN). These are widely developed, besides a mainstream in front-line NN service to range in jobs connected in acknowledging article, like picture categorization. This CNN network uses an image as its input and returns the likelihood of each class. If the object is present in the image, then its likelihood of output is high; otherwise, the likelihood of output for the other classes is either insignificant or low. In contrast to machine learning, the benefit of deep learning is that feature extraction from the data is not necessary.

The classification label of an image shown output and classification together with some measure (probability, loss, accuracy, etc.) after receiving an image as input. As an illustration, a picture of a cat or a picture of a dog might both be categorized as having the class label "dog" or "cat" with some probability.

2.1.1. Object Localization

This approach locates an object's presence in the image and then uses a bounding box to represent it. The bounding box's location is output in the form of (position, height, and width) from a picture that is used as the input.

2.1.2. Object Identification

Entity exposure methods conglomerate roles of item communize by picture labelling. They accept the picture in the form of inputs and outputs many enclosing cases, each of which has the class label as shown in figure 5. Additionally, to multiple category communize, these logics are able to manage things with numerous happenings.

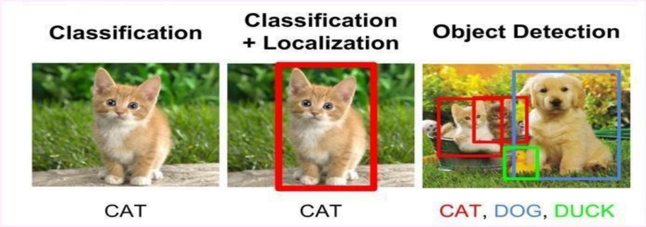

Figure 5. Difference Between Classification, Localization and Detection

2.1. Two-Stage Target Detection Framework

2.1.1 R-CNN

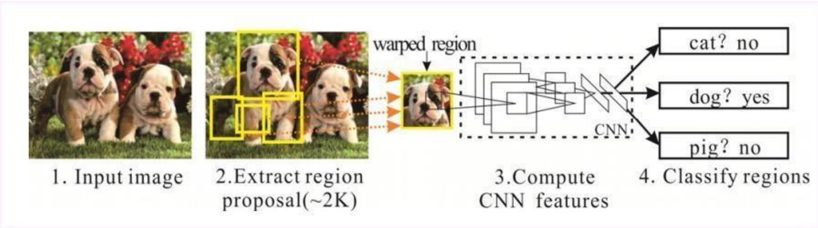

Figure 6. R-CNN Architecture

The R-CNN fixes significantly enhance accuracy and initiated with discerning quest for obtain about two thousand areas approvals in every picture which helps to identify by matching the new idea with the old one which rises the system complications, hence an ineffective one shown in figure 6. An identified picture given to SVM differentiator which separates the properly clambered to set at prefixed path. Lastly, a direct reversion ideal is qualified to bring ready the bouncing case reversion method. Also, clambering the area suggestion right to a prefixed path in feature vector can change the picture.

2.1.2 SPP-Net

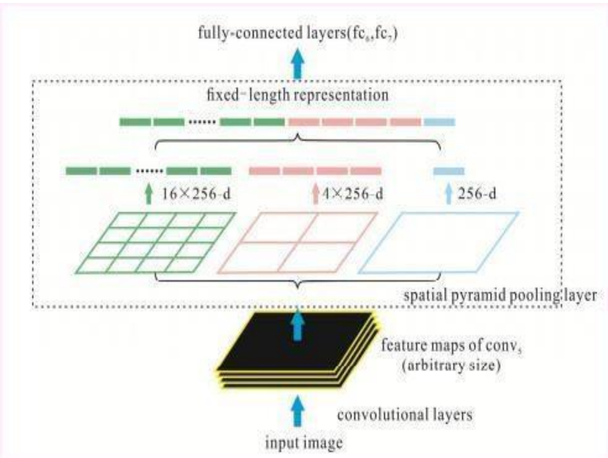

Figure 7. SPP-Net Architecture

SPP - Net only executes the best mining in a complete picture, in contrasting with R-CNN's repeated intentions as shown ion figure 7. However, continuously gives a R-CNN's drawbacks:
(i)Complicated multi-step training methods. And (ii)Different SVM classifiers must be tuned, with more repressors needed.

2.1.3 FAST R-CNN

Associated with R-CNN, Fast R-CNN has undergone 3 variations. Initially, it replaces the SVM used in R-CNN's cataloguing with the softmax task figure 8 depicts its structure. The model also uses the pyramid pooling layer in SPP-Net and substitutes the area of attentiveness combining film for the final merging film at an earlier coating in order to transform the feature of the candidate box into a feature map with a defined size for access to the entire connection layer. The CNN network's last softmax classification layer is lastly changed by 2 similar completely linked layers. But it immobile falls short of real-time detection requirements.

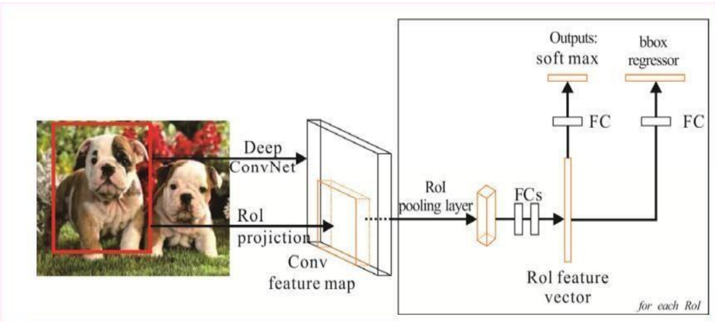

Figure 8. Fast R-CNN Architecture

2.1.4 FASTER R-CNN

A model is collected of 2 units. The Fast R-CNN discovery technique with totally CNN that is castoff to produce with area schemes are illustrated in figure 9. In 2 units share a set of earliest version. A picture will be transmitted via the CNN net which gives to the previous version at a very end. In order to create a higher-dimensional article map, the picture is transmitted forward to the specified CL in a side, Map signal given to RPN network as well. Even though Faster R-CNN has good detection accuracy, real-time detection is still not possible with it

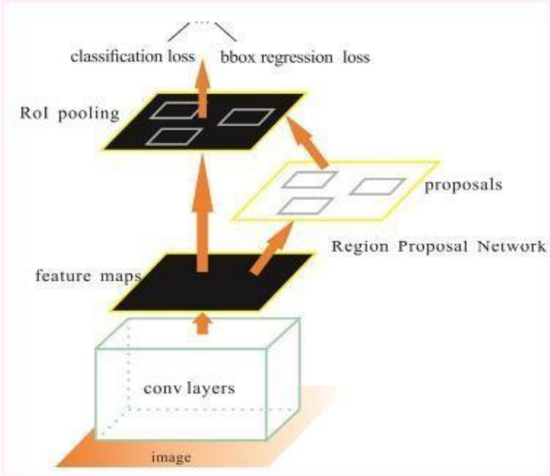

Figure 9. Faster R-CNN Architecture

3. Results and Discussion

The proposed system for the prevention of human-animal conflicts using artificial intelligence (AI) techniques involves the following components:

Data collection: Data will be collected from various sources, including cable imagery, GPS tracking, and wildlife monitoring systems. Signal will help to develop foretelling copies which is found in areas which conflicts are expected to happen.

Predictive modeling: Machine learning techniques will help to develop identifying scheme to develop designs with fashions in wildlife behavior and human activities. These models will be trained on historical data and will be used to predict future conflicts.

Early warning systems: AI-powered sensors and cameras will be installed in areas where conflicts are likely to occur. These sensors will detect and identify animals in real-time, allowing authorities to respond quickly and effectively to potential extortions.

Decision support systems: AI-powered choice provision schemes will help for aid in decision-making processes related to wildlife management. These systems will analyze data from various sources and provide insights that can be used to make informed decisions about wildlife management policies and practices.

Community engagement: Complementary measures, such as community engagement and education, will be used to raise awareness and promote understanding of the importance of wildlife conservation and conflict prevention.

3.1. Architecture of the Proposed System

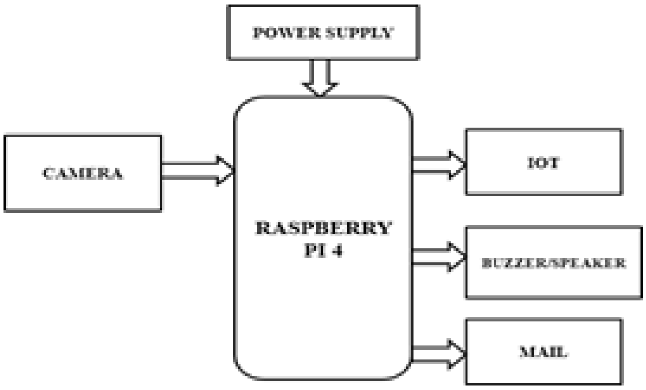

Figure 10. Architecture of the Proposed System

3.2. Training Model

3.2.1 Collection of Data

Animal pictures must first be acquired in order to develop data. We gathered images of six distinct animal species: lions, bears, peacocks, tigers, and elephants as shown in figure 11.
To create a training module, we gathered at least 500 images of a single animal class. Therefore, we took roughly 3000 photographs in all. We selected 150 distinct pictures for each class to test for each picture. So, for testing, we gathered 900 images.

Figure 11. Collection of Data

3.2.2 Image Labelling

In order to create a text document that may be utilized to design a training module, data must be tagged after collection. After accessing the photos, a bounding box is used to choose the ones that include the animal classifications we need. Animals that fall within this category are those that have been boxed. The employed labelling to annotate photos. Animal detection for YOLOv3 and other formats is possible with Labelling as shown in table 1. One image can contain multiple pieces of info. We thus gathered more than 3000 data in 3000 photos. Animals must be divided into classes ranging from 0 to 5 in labelling. Consequently, the following categories were created for animals

Table 1. Classification of Animals in Labelling

Class 0	Elephant
Class 1	Bear
Class 2	Lion
Class 3	Tiger
Class 4	Peacock
Class 5	Chinkara

3.2.3 Training of Model

By developing a training module after labelling the photographs, it utilized Google Colab, a free and open-source programme, to construct a training module as shown in figure 13.

Here, N=2000 epochs.

Where N is the amount of classes and epochs is a manic factor which indicates the periodic knowledge procedure tom executes the periodic observed data's. We need to employ 12000 epochs because we have to train six different classes of animals. At the final and 10,000 epochs, weights files are prepared.

The batch size, sub-divisions, maximum batch size, image size, filer size, number of classes, etc. are configured for the YOLOV3-tiny files.

set=64

classicification=16

area=416

tallness=416

learning_rate=0.001

max_batches=12000

procedures=9600,10800

filters=33

anchors=10,14,23,27,37,58,81,82,135,169,344,319,12

classes=6

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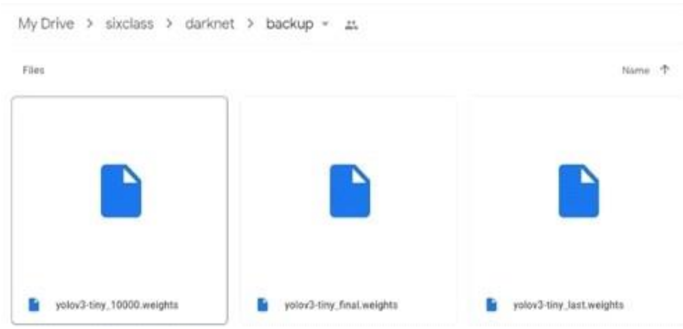

Figure. 13. Weights File is Created

Identified input will be processed earlier updating the internal ideal parameter is determined by the hyper parameter batch size. A forecasts is related to produce expected outcomes with a given data for set's decision, the mistakes were evaluated. A batch number provides information about how many photos will be processed in a batch during a single iteration.

To lessen the GPU's overall RAM utilization, division is provided. The subdivision indicates how many micro batches there are in a batch. Calculating how many small batches the GPU will process at once requires division. The dimensions of the image that we send to the model are width and height. It must be multiple of 32. The knowledge level in manic-constraint which controls the amount by which the loads in the platforms and then modified in respect to the defeat slope. The curve shows decreasing value, and we descend more slowly.

The calculation for maximum batches is

Maximum batches = N * 2000……………………………….(1)

Where, N is no. of classes

(80%, 90%) of the maximum batches are used to compute step size.

Calculation of the number of filters is

Filter= (N+5)*B…………………………………………………(2)

Where, N is no. of classes

B is bounding boxes for every cell which is predicted by YOLOv3 tiny.

The number of B is three since the YOLOv3 small predicts 3 bounding boxes for each cell. Classes are how many classes need to be trained. Most cutting-edge object recognition methods, like the YOLO model, start with anchor boxes as a prior in order to anticipate and localize numerous different items in an image.

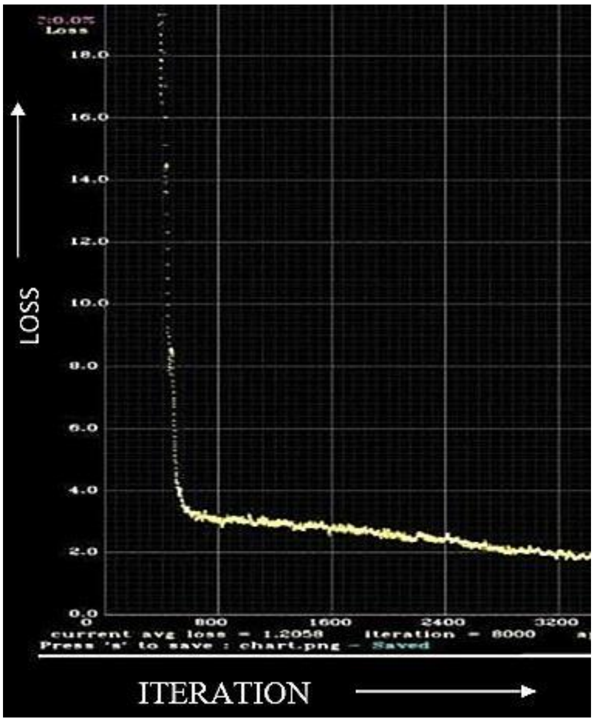

Figure 14. Graph of training Loss Representation

3.2.4 YOLOv3 Object Detector

Modern, real-time object identification technology is used by You Only Look Once (YOLO). Its frame rate is 45 frames per second. There is a second, less accurate version that is faster, running at 155 frames per second. FCNN (Fully Convolutional Neural Network) and Yolo architecture are similar. We utilized a scaled-down version of YOLOv3 called YOLOv3-tiny. It is faster but less accurate than YOLOv3. Since it has fewer layers than YOLOv3, it also takes up less space.

A lightweight target identification technique called Tiny YOLOv3 was used on embedded platforms and is based on YOLOv3. A perfect mass density will be used even though the discovery correctness is worse than YOLOv3. Small YOLOv3 castoff a 13*13, 26*26 2 rate estimate system to forestall a goal and reduced the YOLOv3 article discovery system darknet-53 to a 7-layer standard complication and a 6-layer high Sharing film.

By applying a kernel to each pixel and its nearby pixels throughout the entire image, convolution transforms the image. The convolution process's transformation impact is determined by the scope and values of the kernel, which is a matrix of values. It supports to receive the consolidated output.

3.2.5 Testing of Model

The following are the steps for model testing. The test images are first given labels. After that, the pictures are delivered to a training module as shown in figure 15. The data was tested using ground truth, false positives, false negatives, true positives, and true negatives.

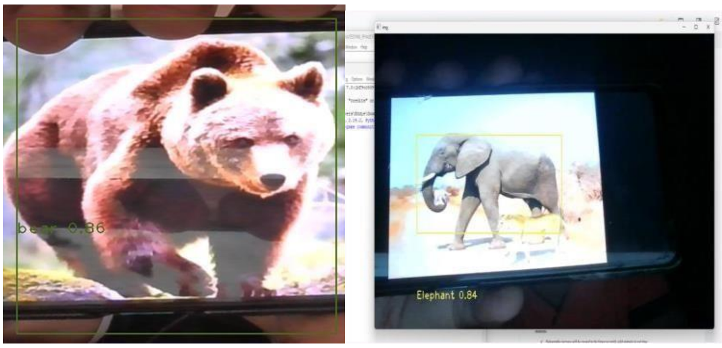

Figure 15. Training Model

a) Ground Truth

In statistical and machine learning, the term "ground truth" refers to evaluating ML solutions to the actual world in order to assess its accuracy. For supervised learning approaches, the phrase "ground truth" relates to the precision with which the training set is classified. This is employed in statistical frameworks to test or disprove research ideas. The concept of "ground truth" describes the procedure of acquiring accurate subjective (provable) facts for this examination.

b) True Positive

It shows consequence for an ideal properly forecasts an optimistic period. If IoU thresh hold, classify the object detection as True Positive (TP).

c) True Negative

A true negative is an output where the model correctly predicts the negative class. It is not an efficient to predict the picture.

d) False Positive

This method produces the wrong prediction and not an efficient and predicts the positive

e) False Negative

This model incorrectly forecasts an undesirable lesson. This ideal is unsuccessful for prediction of an item.

f) Precision and Recall

It gives the state to assess the recital. Exactness is the fraction of the positives that are properly recognized by the ideal ended entire optimistic proceedings

3.2.6 Implementation of Software and Hardware

In this proposed system, collected data for six animal classes—lions, elephants, tigers, peacocks, bears, and chinkaras as shown in figure 16. After many trails, accumulated more than 3000 animal-related data points. The gathered pictures are given new names first. The data are successfully learned in YOLOv3-tiny using Google Colab. We also collect 150 more photos for each class for model testing. As a result, we collect 900 more images for data analysis. Begin the testing for the collected data after the training model has been generated.

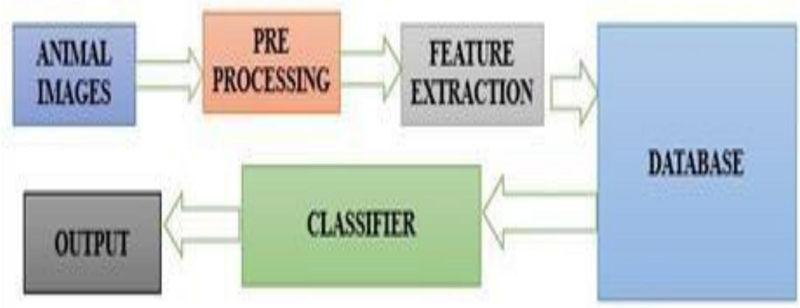

Figure 16. Block Diagram of the Model

Therefore, initiated to train two classes of data followed by its successful training, we trained 3 classes, and so on until we had trained 6 classes. Collected data randomly and then labelled them with the labelling programme file's standard extension. The model was trained and we acquired error as a result of the frequent disconnections throughout the data training. The image was then tested using Python and OpenCV. The gather information from 200 photos for each class, the processor receives the model and verify the several stages in order to transfer a model.

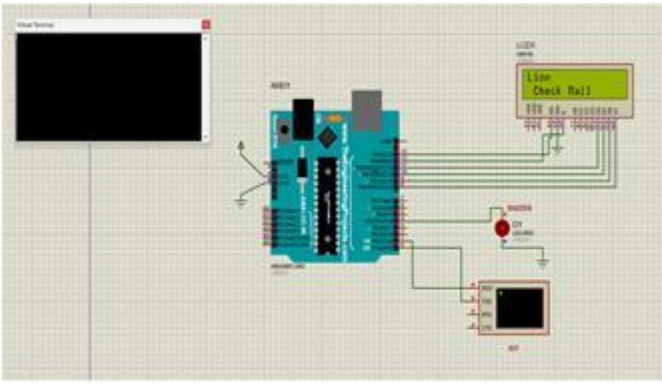

Figure 17. Simulation of Hardware in Proteus

The figure 17 shows the output of our model using proteus. When the animal is noticed the label of inborn is exposed. The bounding box shows the detected animal in the captured image as shown in figure 18.

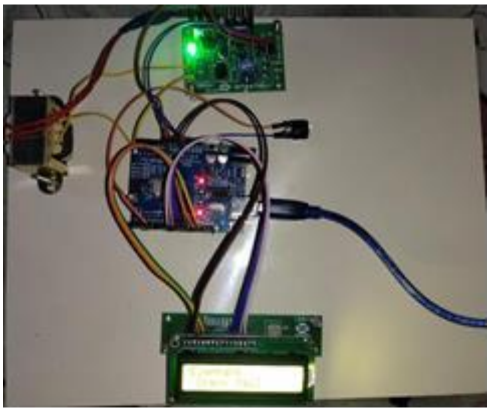

Figure 18. Hardware Setup of Proposed System

4. Conclusion

As the number of people increases worldwide that invade the desert. In addition, wildlife determines altered locales then blocked immigration pathways. Battles among individuals also remote creatures over nutrition besides territory must gotten worse over time, harming people physically and financially through personal assaults and cattle predation. In defenses and out of retaliation, wildlife can be killed. Conflict between people and wildlife exists everywhere. From elephants eating Indian crops to tigers preying on Nepalese cattle to polar bears raiding Arctic villages' waste bins. Also, crucial to find a harmless way to coexist with wildlife. Numerous tools require stayed fashioned for reducing creatures and individual struggle, in addition to education, return- distribution structures, besides better terrestrial custom plan. These include trench and electric fences that serve as barriers between people and wildlife. Wild animals are kept away from human communities and their valuables by flashlights and guard dogs. Though, the animal might suffer harm as a result. Therefore, a offered design assurances a innovative boards to guaranteed protection of trespassing desolate animals then the people clearances, avoiding compromising both safety measures.

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