

An Effective Stray Animal Detection and Crash Prevention System using Deep Learning and Internet of Things

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Abstract— Road crossing or at road side stray animals like cows and buffalos are usually observed in India. Such animals creates critical situations on roadways due to the collision. According to data obtained from the veterinary department of Nagpur municipal corporation approximately 3,127 cattle were injured and at least 30% of them died immediately and after a few days of hospitalization. This paper showcase a solar powered deep learning and IoT enabled early warning system which could detect the stray animals and send an alerts to the vehicles on road. The IoT cloud platform and dashboard delivers the information of accident prone zone. The trained stray animal detection model in the present system could predict 86% to 90% true positive results with 91% accuracy on real world camera feed. The 433 Mhz RF transmitter in the system is capable to send alert up to 110m.

Index Terms— Deep Learning, IoT, Animal Detection, Road Safety, YOLO

I. INTRODUCTION

The purpose behind the design and development of the system for road safety engineering is a vehicular system equipped with the vehicle which is capable to receive the alerts from the base station after the detection of stray cattle. In the developing country like India stray animals are often observed on the roadways. They are usually seated or standing exactly at the middle location of road. In some cases it is also observed that they have entered on roadway at any moment. Therefore these stray animals are must visible to the drivers of vehicle such a way to control the speed of vehicle. Also the vehicular drivers must know he is going to enter in zone where the stray animals present. The critical situation arises at day well as night when the drivers are unable to control his vehicle during sudden appearance of animal in front of his vehicle. Thus it creates complicated scenario due to collision between the vehicle and animal on the roadway. Here our work focuses to nullify the mishap between stray or domestic animals and vehicle. According to veterinary department of nagpur Municipal Corporation and news by TNN more than thirteen thousand animals were injured during 4.4 years of span. Out of the total count of injured animals more than three thousand were cattle. It is observed that around 3,442 stray animals were injured year 2020-21 due to covid lockdown, while the figure was 4,262 in 2019-20.

The paper focuses on a wireless warning station, which plays an important role by transmitting the warning kind of information to the driver of vehicle who are entering in the wireless zone. The LED active road sign in the

system is capable to give flashing indication to the driver of vehicle. This LED active road sign could be deployed at roadsides, which is visible to the driver. The special LED active road studs deployed on the roadway are also going to flash after the detection of cattle in the surveillance zone. To energize the system, it consists of power management system which can provide power from electricity line or from solar and UPS battery backup scheme. The convolution neural network based YOLO deep learning algorithm deployed with warning station for animal detection and recognition in the surveillance zone. The system also consist a wireless receiver station that can be deployed on the vehicles dashboard or integrated in the infotainment section. So that it can give indication or warnings to the driver. The IoT and cloud connectivity platform in the system has the capability to provide details of zone, date and time where the animals detected.

II. RELATED WORK

Diversified research works have been carried out from last decades on animal detection and surveillance system to avoid human-animal conflict. T.S. Balaji et.al [1] proposed an automatic wild animal detection system which consists a small RSSI or Zigbee tag deployed on animals' ears or in their bodies. The receivers integrated into the crossing area could debug the embedded tag and stop the vehicles when wild animals are near the crossing area. Sandeep Kumar Singh et.al [2] researched into animal-human cohabitation problems using machine learning and wireless fibre access networks (FiWi) integrating cloud and edge computing. The proposed system can detect rail or road crossing wild animals near the road or rail track by using wireless sensor networks and alerts vehicles. Hung Nguyen et.al [3] proposed a framework of automated wildlife monitoring system for wild animal recognition which utilizes single labeled dataset obtained from wildlife spotter project. The trained deep convolutional neural network architecture in the system had the capability of filtering and identifying species of animal automatically. They achieved 96.6% accuracy in detecting images of animals and 90.4% in identifying the three most common species of the entire set of images of wild animals. The wildlife road crossing problem investigated by Federico Viani et.al [4]. Their detection technique was based on integration of doppler radar and wireless sensor network technology. The real time static or flashing road signs based driver notification system introduced. The radar detection system could transmit the information collected to the control unit for data storage and additional statistics. The cross frame temporal patch verification method proposed by Zhi Zhang et.al [1] which could determine true animals or background patches. The comparison has been carried out with faster RCNN and obtained 4.5% improved detection accuracy. An animal detection model using self-learned Deep Convolutional Neural Network (DCNN) features proposed by Gyanendra Verma et.al [2] and classification was carried out with the help of KNN, SVM and ensemble tree machine learning algorithms. Experimentations were carried out on standard camera trap image datasets. An on road animal detection by deploying cameras on road and KNN learning model proposed in Brazil. Atri Saxena et.al [3] proposed animal detection using SSD and R-CNN neural network architectures with mAP of 80.5% and 82.11% respectively. Sachin Sharma et.al [4] proposed an animal detection on Indian roadways using HOG feature descriptor used in computer vision and image processing. With these features and boosted cascade classifier system could give 82.5% animal detection accuracy. Tibor Trnovszky et.al [5] proposed Convolutional Neural Network (CNN) for the classification of four target classes of animals. They compared the method with other well-known image recognition methods like PCA, LDA, LBPH and SVM. Hung Nguyen et.al proposed the automated wildlife monitoring system with DCNN for wild animal recognition and identification. They obtained 90.5% identification accuracy for the wild animals found in South-central Victoria, Australia.

III. SYSTEM ARCHITECTURE

The functional block diagram of deep learning, IoT and RF based stray animal detection and early warning for road safety is shown figure 1.

The system comprises a computerized warning station where central computer interfaced with vision sensor, driver unit, antenna and transmitter section, and charging unit. Solar cells, power bank and battery charging unit are comes under the power management scheme mainly used to provide power supply to the system. The charging of power bank in this scheme is carried out by using solar cells and charging unit. The power management section could also be connected to local electricity line therefore the system can work on electricity line as well as on solar and battery backup mechanism. The sufficient features are delivered to the computer with the help of wide field of view night vision infrared sensor which further processed by deep learning algorithm. The fast light weight YOLO version five trained deep learning algorithm utilized for animal detection and recognition in the surveillance zone. The antenna and radio wave transmitter block is used to send the warning signals to the vehicles on the roads.

The deep learning algorithm detects stray animal in the surveillance zone. Upon the recognition system also turns ON flashing of LED active road sign and road studs through driver unit. The receiver system comprises 433Mhz carrier frequency based RF receiver and alarm driver module as shown in figure 2. After the reception of warning radio signals form warning base station receiver system turns ON the alarm.

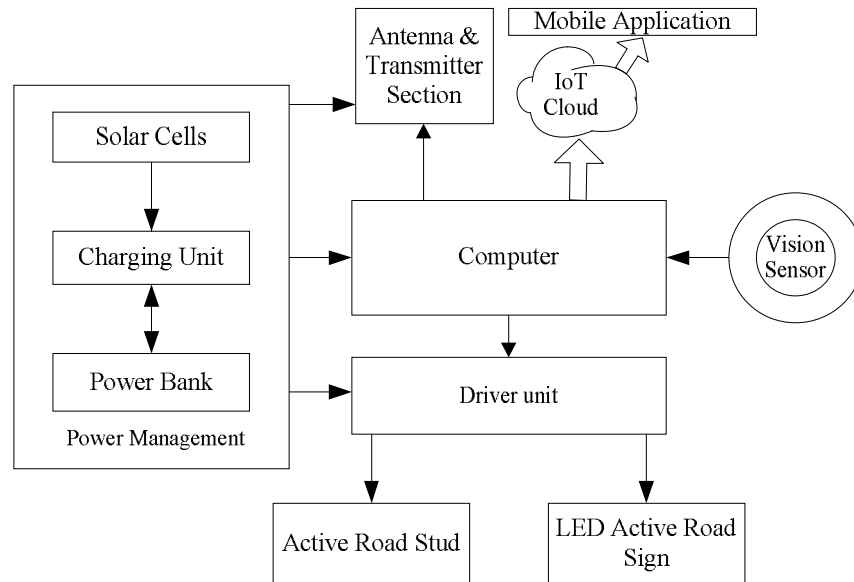


Fig. 1: Block Diagram

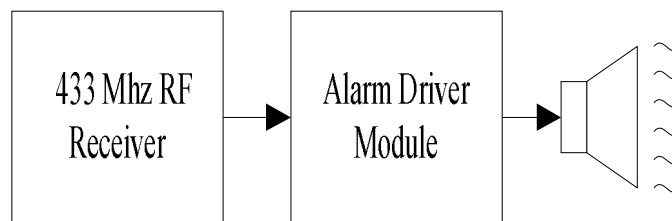


Fig. 2: Receiver system for vehicles

IV. SOFTWARE IMPLEMENTATION

The flow diagram of the stray animal detection and early warning system is shown in figure 3.

At step 1, the deployed vision sensor in the system continuously monitors the surveillance zone by using its wide field of view.

At step 2, the system undergoes through movement detection in the scene and video capturing process if any movement get detected in the scene.

At step 3, the computer vision and deep learning model processes data frames for the feature extraction, the algorithm utilizes the acquired features to recognize the stray animal in the scene.

At step 4, the decision is made either the animals are present in the scene or no. In the absence of stray animals in the processed frames, the system continues with step 1 for monitoring and if any animal get detected then system turns ON the flashing of LED active road stud and active road sign until the count become zero. Simultaneously system sends the alert signal wirelessly to the vehicle on the roadway and also the details of zone are highlighted on dashboard of Ubidot IoT cloud. The location and accident prone zone also visible though dashboard by mobile device.

The overall system arrangement is shown in figure 4. The output of the control panel (enclosure) is connected to junction box which is deployed at the bottom of pole. The connector terminals inside the junction box have been used to connect LED active road sign and LED active road stud by using connecting wire. The LED active road sign has deployed on the pole and road studs are installed on the roadway by burring the shank of stud. The buried connecting wires passes through an underground conduit which is used to house and protect the wires. The solar cells are deployed at the top of main control panel.

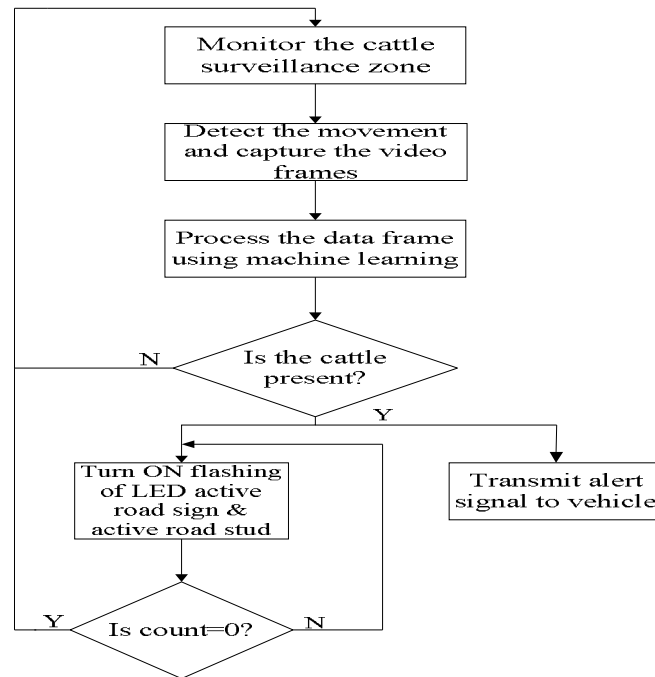


Fig. 3: Flow Diagram of the System

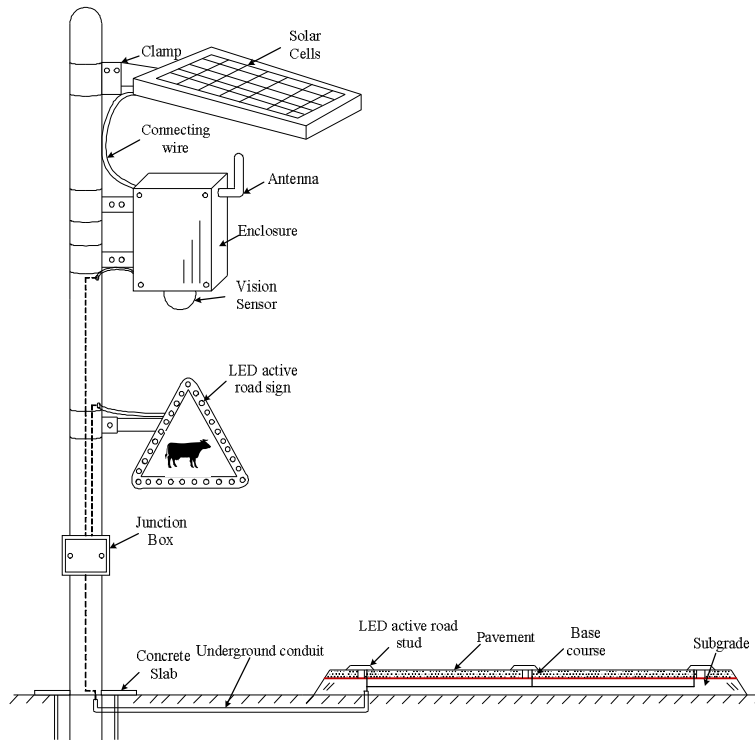


Fig. 4: System Arrangement

V. OBJECT DETECTION PROCESS

The object detection process in this work presents an animal detection model specifically for wandering stray animals observed on the road with a single-stage object detector YOLO version 5. The architecture of the YOLO network is highlighted in figure 5 and is divided into three parts such as the model backbone, the model neck, and the model head.

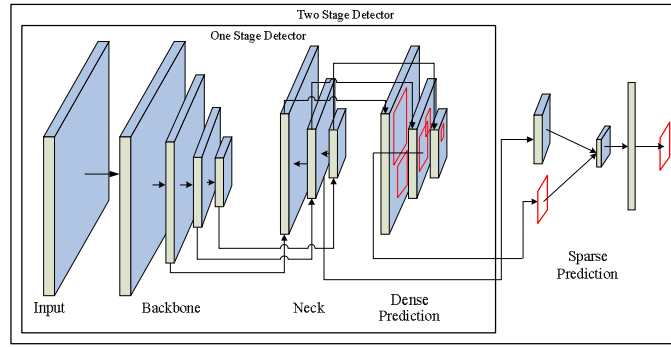


Fig. 5: Yolo Network

The utilization of model backbone to extract salient features in the input frames. The Cross Stage Partial Networks (CSP) at this part has the capability to extracts rich informative features from an image. It improves the processing time of the models with the deeper network. The Path Aggregation Network (PANet) in the next part of single stage detector generates feature pyramids. These feature pyramids enhances the object scaling in the model. As a result model with different sizes and scales could identify the objects effectively. It also helps to do well with data that is not seen. At the end, the model head uses anchor boxes on features to find objects, and it creates output vectors with objectness scores, class probabilities, and bounding boxes as a result. At the middle and hidden layers of the model's neural network, the leaky ReLU activation function is used, while the sigmoid activation function is used at the final detection layer. The Stochastic Gradient Descent (SGD) as default optimization function is used to optimize the network model. The model's class probability score, objectness score, and bounding box regression score serve as the foundation for the calculation of compound loss. Ultralytics uses binary cross entropy and the logits loss function from PyTorch to calculate loss for class probability and object score. A total of nine stages are involved in the construction of a deep learning model for animal detection and the system for avoiding accidents, as shown in figure 6.

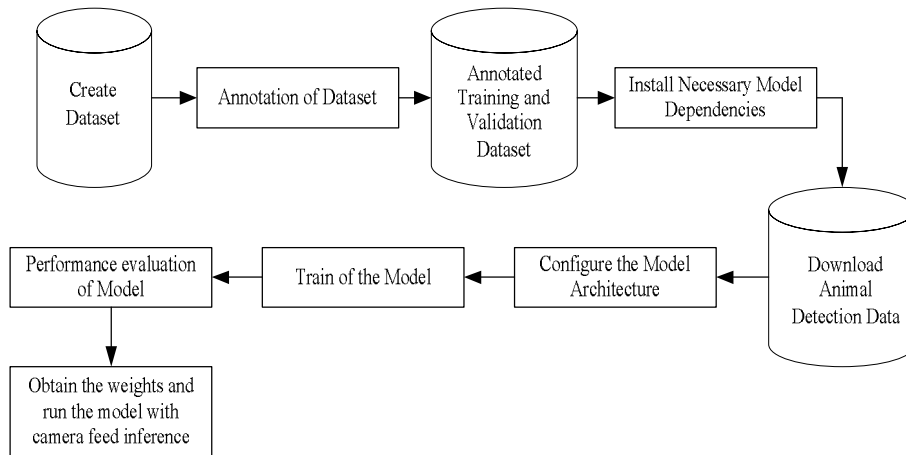


Fig. 6 Stages in Deep Learning Model

A. Dataset Formation

The selections of suitable machine learning model and appropriate dataset have been a crucial step in the analysis of the dataset. As the machine learning model focused on stray cattle detection on Indian roads, other factors like number of animals, their classes and dimensions influence the study directly. In the current work, total 7299 validation samples and 17031 training samples of stray animals observed on roadways are used. The dataset have been created by collecting the images by using camera at day as well as at night time on road ways. Dataset also consist the images acquired from websites and by using image data augmentation techniques like rotate, sheer, noise addition, shift, flip, gray image etc. Random background image samples are further added in the dataset for detection and classification point view. Few samples of data are shown in following figures. Figure 7 shows the excited stray animals at road side and figure 8 where stray buffalos crossing the road dangerously.



Fig. 7 Stray Animals at Road Side



Fig. 8 Stray Buffalos Crossing the Road

The created dataset consist of image samples where almost all the positions of stray animals are covered.

B. Annotation Of Dataset

Using bounding box annotations, supervise the learning of machine learning and object detection is a crucial task. Consequently all the image samples including training and validation are annotated. All cattle types in the dataset are annotated, a label is given for the cattle class, and the bounding box coordinates (x1, y1) and (x2, y2) are obtained because this system is more focused on an animal detection model. Figure 9 depicts four annotated bounding boxes over cattle in one of the annotated images created during batch processing, with "cattle" over the bounding box representing the object's class name.

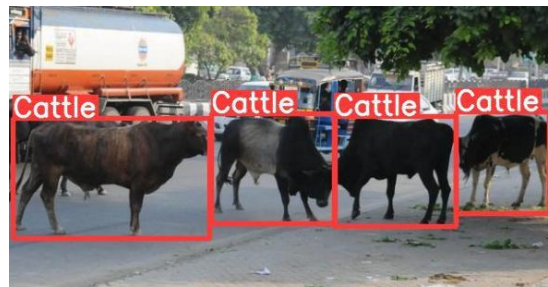


Fig. 9 Test Batch Labeled Image

C. Annotated Training And Validation Dataset

The training and validation subdirectory is where all of the dataset's annotated images are categorized, and the labels for each image are also compiled there. Therefore, the model can now be constructed from the final directories of training and validation, which include annotated images and appropriate labels.

D. Installation Of Model Dependencies

At this stage of the work model the necessary dependencies are installed and written the python program to generate alert message upon the detection of stray animal in the YOLO model repository. The programming environment for the animal detection training and inferences command will be set up in this manner.

E. Download The Data

In the Colab environment, the annotated training and validation dataset and label directories are invoked at this stage. To the train the model in the training environment the appropriate paths of the custom dataset are provided in yet another markup language file.

F. Configure The Model Architecture

The obtain realtime and fast animal detection process YOLO we have chosen small v5s model architecture and configured for fastest model using yolov5s.yaml file.

A. Train The Model

The stray animal detection deep learning model has been trained at various batch size and epoch values with custom dataset and GPU accelerator with T4 type on colab. Other arguments such as image size (640x480), data path, model configuration, custom path for weight were set during training process. The obtained weights are stored for further inference process. The performance of model evaluated by compiling the training results. The

test batch stray animal prediction result of model shown in figure 10. The animals in the frame are predicted and percentage of prediction shown above the bounding boxes of each stray animal.

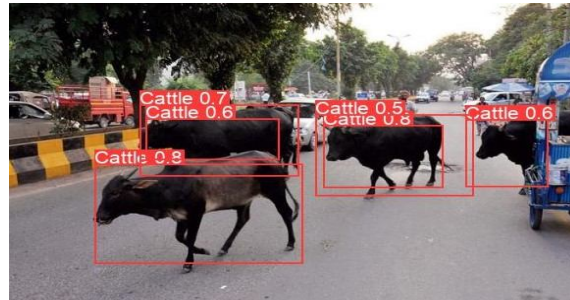


Fig. 10 Test Batch Predictions

H. Performance Evaluation

The performance evaluation of the trained deep learning stray animal detection has carried out by considering the validation matrices. Figure 11 depicts the box loss and objectness loss, which indicate the model's accuracy in locating the predicted animal's center and covering it with the predicted bounding box. In a RoI, where high objectivity indicates that the image window is likely to contain an object, objectness measures the likelihood that the animal exists. After training, the model shows improvements in precision, recall, and mAP before flattening after approximately 100 epochs, as shown in figure 12. Until around 100 epochs, all losses in the validation data show a rapid decline.

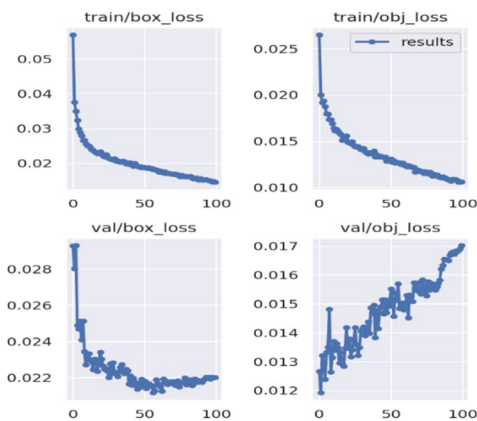


Fig. 11 Plots of Box Loss, Objectness loss over the training epochs

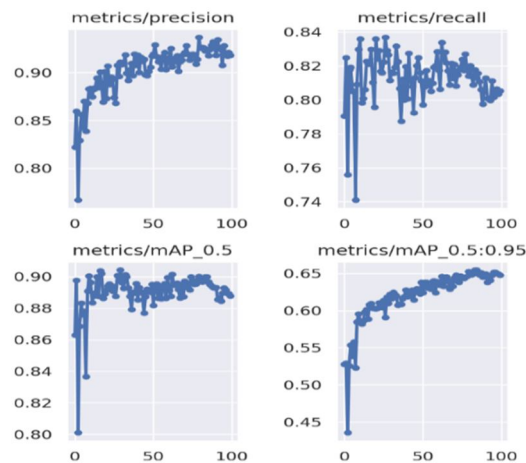


Fig. 12 Plots of Precision Recall and Mean average precision (mAP) over the training epochs

Figure 13 depicts the response for F1 score versus confidence. It's value varies from 0 to 1 and value 1 indicates highest accuracy. The result shows obtained optimization accuracy of 0.87 at confidence value 0.09. According to the graph, the confidence value 0.87 indicates the probability that an anchor box contains an object. Figure 14 depicts the precision versus confidence plot. Here precision is 1 at 0.95 confidence score. The model's performance is evaluated using the precision versus recall plot. Figure 15 shows the good response of precision and recall of our model. The plot obtained for recall and confidence is shown in figure 16. Accuracy, sensitivity and F-measure performance metrics are chosen to evaluate the performance of the model.

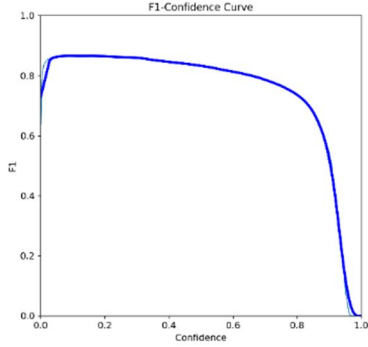


Fig. 13 F1 vs Confidence Plot

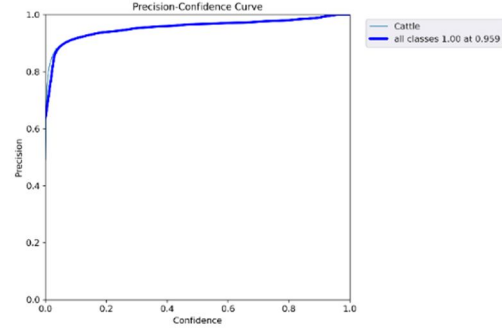


Fig. 14 Precision vs Confidence Plot

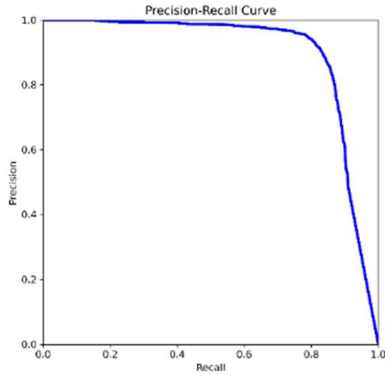


Fig. 15 Precision vs Recall Plot

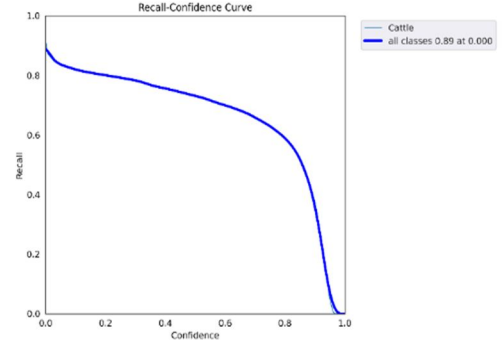


Fig. 16 Recall vs Confidence Plot

$$F - \text{Measure} = \frac{2 * TP}{(2 * TP + FN + FP)} \quad (1)$$

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (2)$$

$$\text{Sensitivity} = \frac{TP}{(TP + FN)} \quad (3)$$

The model's performance is evaluated using four crucial matrices: True Positive (TP), False Negative (FN), True Negative (TN), and False Positive (FP). The metric F-measure Eq. 1 is the ratio of twice the number of true positive to the summation of twice the number of true positive, false negative and false positive. The performance metric accuracy Eq. 2 is the ratio of total number of true positives and true negatives to the all four metrics. Sensitivity Eq. 3 is the number of true positives to the sum of true positives and false negatives. Table 1 shows the results of three performance metrics Accuracy, Sensitivity and F-measure and to measure the performance of the model.

I. Run The Model With Camera Feed Inference

The stray animal detection model in the work trained using custom ground truth image samples. The mean precision, recall and mAP acquired during the training of the model. Finally the compiled weights acquired at each iteration are further used to test the model for animal detection with real time camera feed video inference as well as sample videos and image dataset.

TABLE I. PERFORMANCE OF ANIMAL DETECTION MODEL

Batch Value	2	2	2	3	10
Epoch Value	60	100	150	150	100
Precision	0.64	0.88	0.87	0.84	0.9
Recall	0.66	0.70	0.76	0.73	0.81
mAP 0.5	0.63	0.78	0.83	0.78	0.89
TP	0.85	0.77	0.82	0.82	0.81
TN	1	1	1	1	1
FP	0	0	0	0	0
FN	0.15	0.23	0.18	0.18	0.19
Accuracy	0.92	0.88	0.91	0.91	0.905
Sensitivity	0.85	0.77	0.82	0.82	0.81
F Measure	0.91	0.87	0.90	0.90	0.90

VI. HARDWARE IMPLEMENTATION

The real-time stray animal detection using deep learning model and internet of thing developed in this work. The prototype of warning station depicted in figure 17. The external front cover of control panel and enclosure with supporting stand shown in first part and the internal hardware components in the second part. The solar cells, Battery section with charging module, 433 Mhz RF Transmitter with antenna and HT12E encoder, Road sign LED cluster, LED driver with wifi feature, CPU with interfaced camera at bottom are the major sections of the system.

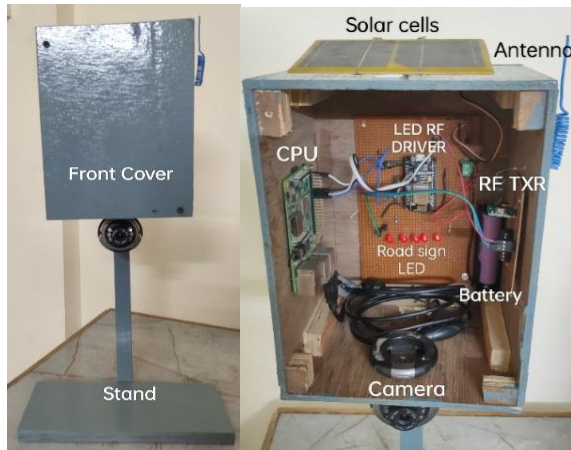


Fig.17 Prototype of Base Station

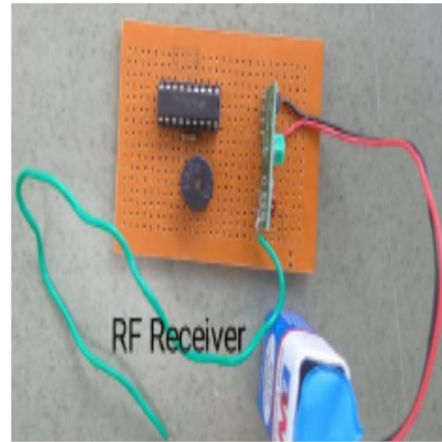


Fig. 18 433Mhz RF Receiver with Alarm

Figure 18 shows the 433 Mhz RF receiver hardware with HT 12D decoder and alarm. The receiver and alarm module could be integrated in the vehicle to alert the driver of vehicle.

VII. RESULTS

The deep learning and IoT enabled stray animal detection and early warning system in the field of road safety engineering is presented. The deep learning model built in this work is efficient one in terms of mean accuracy of 90.5%, mean sensitivity of 81.5% and mean F-measure of 89.6%. The test have been carried out with the model on Intel, Core2 Duo CPU with 2.93 GHz and 2 Gb of RAM by considering various light conditions, animal poses and real world critical road conditions. In free space approximately 90m to 110m distance achieved between warning base station and RF receiver upon detection stray animal by the warning station. The coverage distance could be improved by proper designing of the antenna. Figure 19 and figure 20 illustrates the detection of stray animals either in sitting or standing position and herd of animals at road side respectively. The model could adroitly detect the animals in occluded situation as in figure 21. Figure 22 depicts the detection result at poor light situation. The red color bounding box shows the detection of localized animals in the scene and the values at top right corner are nothing but the accuracy of the recognized object.

The dashboard of Ubidots IoT cloud platform and the results are shown following figures. Figure 23 depicts the zone wise warning message obtained from base station and figure 24 depicts the location details of zone where active stray animals recognized by the warning station. The dashboard could be visible to any wired or wireless device available in the intranet.

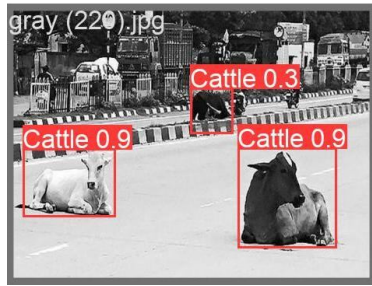


Fig. 19 Seated Animals

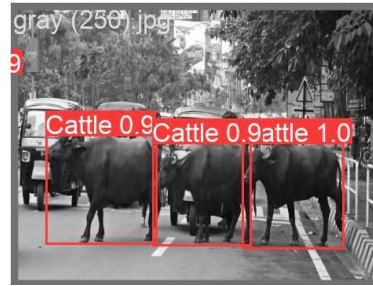


Fig. 20 Herd of Stray Animals



Fig. 21 Animals in Occluded Situation



Fig. 22 Detection at Low Light Condition

Animal Detection Zone No:3	
VARIABLE NAME ↑	ZONE NUMBER
warning-animals-not-present-in-zone-no.:	3.00
warning-animals-present-in-zone-no.:	3.00

Fig. 23 Warning Message on Dashboard



Fig. 24 Location of Stray Animals

VIII. CONCLUSION

This research work focuses on design and developments in road safety engineering using deep learning, internet of things and RF communication. Such kind of system could minimize the number of accidents and injuries on the roadways due to the collision between stray animals and vehicles. A standalone stray animal detection and early warning system presented in the paper using deep learning model and IoT. The wireless base station deployed on the pole in the work could continuously monitor and warn the vehicles on roadway. The trained custom model has achieved 90.5% detection accuracy for the domestic animals usually found on Indian roads. The developed system could be improved in terms of coverage range with help of LoRa technology, IoT cloud platforms like AWS, Microsoft Azure and other classes of stray animals in the deep learning model.

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