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IoT-BASED INTELLIGENT SYSTEM FOR PROTECTING AGRICULTURAL CROPLANDS FROM LIVESTOCK AND VERTEBRATE INTRUSIONS

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Abstract: in this research cattle, sheep, goat, rat and from birds consists of five targeted classroom in real time in mode to detect intended computer vision, Internet of Things (IoT), edge/ cloud calculation and GSM/4G communication technologies based intelligent monitoring system offer is being done. Simple image classification from the methods different accordingly, proposal done system in video foot-age one of time in the room one how many the object localization to do, to classify and counting for one step by step object from the detector uses. Next in stages many with object observation algorithm of objects consecutively trajectory of movement in frames and existence duration Virtual field border using of the object really good to the field entered or only his/her outside moving differs.

Keywords: Internet of Things, smart village farm, YOLO, GSM/4G, edge computing, computer vision.

I. INTRODUCTION

Village farm working to release biological, climatic and anthropogenic of factors wide circle impact shows. This because of crops protection to do only plant diseases and insect pests against fight with is not limited. Many village farm in the regions livestock animals and vertebrate pests crop to the fields uncontrolled entrance also harvest amount and to the quality negative impact shows.

Offer being done approach main scientific and practical aspects of the following consists of: crop fields for five classy object detection model formation; object detection and many with object observation integration; virtual field border through real intrusion automatic confirmation; many factorial danger assessment model working exit; decision acceptance in doing animals number, direction of movement and on the field stay duration into account to take; GSM/4G based eventful information transmission organization to do; object to the class suitable differential answer strategy working exit; lie warnings and unnecessary deterrent activations reduce

II. LITERATURE SURVEY

Delaware and co-authors based on IoT and YOLOv8 animals' field to the field real -time input in mode detection system offer [1]. This research modern object detectors village farm monitoring and automatic warning with integration to do opportunities showed. Miao and co-authors animals' intrusion detection based on edge computing for smart village farm system offer [2]. This work field in the territory of the image one part local again work continuous cloudy to contact was need reduce showed. Balakrishna and co-authors IoT and with a car to study-based village farm crops animals from intrusion protection to do system research [3]. Such research automatic detection and wireless warning technologies permanent human to follow need reduce possible confirms. Araújo and co-authors complicated farm under the circumstance's cattle detection the issue research [4]. In this context, changes in illumination, animal body posture, background characteristics, and partial occlusions are important factors affecting animal detection. Modern lightweight YOLO architectures less calculation from re-sources used without real time in mode the sheep detection opportunity shows [5]. Goats monitoring is similar to the complexities has. Remotely or partially closed in case sheep and goats external appearance similar to be possible. Therefore goats in automatic monitoring many with object detection from models use efficiency re-search made [6]. Artificial intellect and thermal to describe combined modern research based on YOLO models using rats in real time in mode detection opportunity [7]. Birds detection is also small and fast moving objects with related complicated task Upendra and co-authors YOLO and installed calculation to their devices based automatic the birds intimidation system offer [8]. Duttenhefner and co-authors and village to the farm damage delivery person black the birds drone flight apparatus images using automatic definition, classification and to count research did [9].

Existing systems primarily focus on detecting the presence of animals (Table 1). However, detection confidence alone does not indicate the actual threat to crops. Therefore, this study introduces a unified risk assessment mechanism combining intrusion depth, movement direction, group size, residence time, recurrence frequency, and detection confidence.

Table 1. Crop monitoring of fields approaches comparative analysis

Study	Detection	Tracking	Geofence	Risk assessment	IoT/GSM	Event-driven
Delwar et al. [1]	✓	-	-	-	✓	-
Miao et al. [2]	✓	-	-	-	✓	- / limited
Balakrishna et al. [3]	✓	-	-	-	✓	-
Upendra et al. [8]	✓	-	-	-	-	-
Bapat et al. [9]	limited	-	-	-	✓	-
Purposed model	✓	✓	✓	✓	✓	✓

III. METHODOLOGY

Image represents the general functional scheme of the process of detecting foreign objects in agricultural fields, analyzing their movement, and issuing warnings based on the level of risk (Figure 1). The process initially begins with receiving data from cameras, infrared devices, and various sensors installed in the agricultural field. The resulting video frames are transmitted to an edge computing device (Edge Device). This device captures video frames, detects objects using the YOLO algorithm, and monitors their movement using multi-object tracking algorithms.

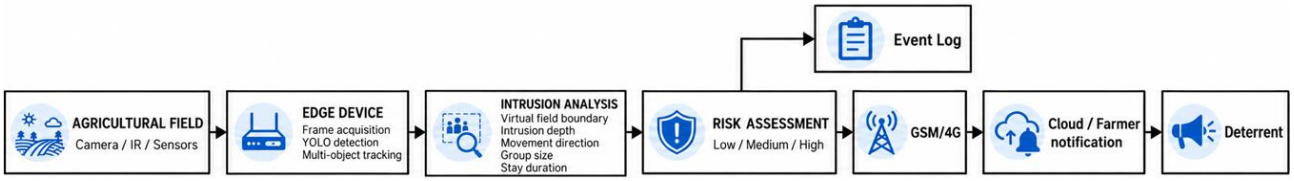


Figure 1. Overall architecture of the proposed intelligent crop-protection system

The next stage is Intrusion Analysis. This detects whether the object crosses the boundary of the virtual field, the depth of entry into the field, the direction of movement, the number of objects or groups of animals, and the duration of its stay in the field. Based on these indicators, the risk level of the event is assessed as low, medium, or high. The detected event is recorded in the system's Event Log. If necessary, information is sent to the cloud platform or to the farmer via the GSM/4G communication network. After the appropriate warning is delivered to the user, if necessary, deterrents are activated to keep the animal or foreign object away from the area (Table 2).

Table 2. Targeted of classes main features

Class	To the crop potential impact	Home detection problem
Cattle	Crop consumption to do, to see to water, to irrigate their possessions break	Large object, partial blocking
Sheep	Group to be crop with nutrition	Dense in the group detection
Goat	Leaf, stem and sprouts consumption to do	Sheep with visual similarity
Rat	Seed, sprout and grain damage	Small object, night detection
Bird	Seeds, grains and to fruit damage	Small and fast-moving object

Model's lie detections reduce for teaching in the data people, cars, dogs, plants movement and empty field images such as target not been save scenes too to the goal according to. Dataset real field conditions reflection provider following the images own inside to receive must various seasons: daytime and night conditions; various camera distances; partially closed objects; animals different colors and dimensions; alone and group cases; moving and motionless objects; various crop backgrounds (Table 3).

Table 3. Composition of the experimental dataset

Class	Images	Instances	Day	Night
Cattle	1.450	1.820	1.040	410
Sheep	1.680	3.560	1.210	470
Goat	1.520	2.410	1.080	440
Rat	1.380	1.980	420	960

Bird	1.820	4.280	1.390	430
Total	7.850	14.050	5.140	2.710

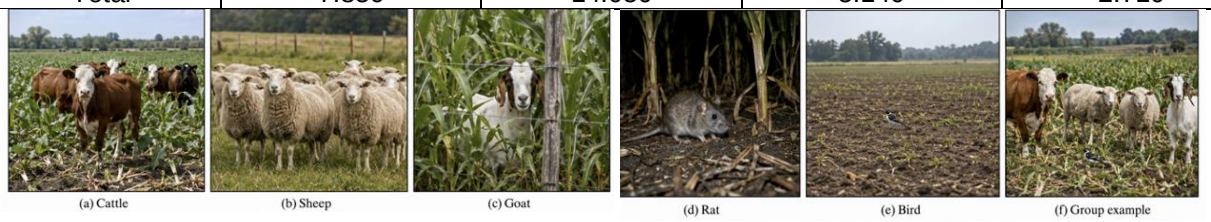


Figure 2. Representative samples of the five target animal classes

The experimental dataset contained 7,850 images with 14,050 annotated examples from five target classes: cattle, sheep, goats, rats, and birds. Of the total images, 5,140 (65.48%) were acquired in daytime conditions and 2,710 (34.52%) were acquired in night or low-light conditions. Where:

$$D = D_{train} \cup D_{val} \cup D_{test} \tag{1}$$

and

$$D_{train} \cap D_{test} = \varnothing \tag{2}$$

where D denotes the complete dataset; D_{train} denotes the training subset used to train the model; D_{val} denotes the validation subset used to monitor model performance and tune hyperparameters during training; D_{test} denotes the test subset used for the final independent evaluation of the trained model; $\cup$ denotes the union of the subsets; $\cap$ denotes the intersection of the subsets; $\varnothing$ denotes the empty set. As data augmentation horizontal reflection, small in the corner twist, brightness and contrast transform, scale, motion blur, Gaussian noise and partially the barrier from modeling use possible. This in the matter simple image from the classification according to object detection necessary, because one in the frame one of time in itself one how many ani-mal there is to be possible. Home architecture to the YOLO family as belonging one step by step object from the detector use offer YOLO architectures speed and localization accuracy between acceptable ratio providing, village farm and animal monitoring in their du-ties successful used [1, 10]:

$$O_t = \{o_1, o_2, \ldots, o_{Nt}\} \tag{3}$$

where t is the video-frame time index; O_t is the set of all objects detected in frame t; O_i is the i-th detected object; N_t is the total number of objects detected in frame t. Each detected object o_i is represented as

$$o_i = (b_i, c_i, p_i) \tag{4}$$

where b_i is the bounding box of the detected object; c_i is the predicted object class; $p_i \in [0,1]$ is the confidence score assigned by the detection model. The object class is defined as

$$c_i \in \{cattle, sheep, goat, rat, bird\} \tag{5}$$

The bounding box is represented by

$$b_i = (x_i, y_i, w_i, h_i) \tag{6}$$

where x_i is the horizontal coordinate of the upper-left corner of the bounding box; y_i is the vertical coordinate of the upper-left corner; w_i is the width of the bounding box; h_i is the height of the bounding box.

For intrusion analysis, the bottom-center point of the bounding box is used as an approximate ground contact point of the detected animal:

$$g_i = (x_i + \frac{w_i}{2}, y_i + h_i) \tag{7}$$

Where g_i denotes the bottom-center point of the bounding box of the i - th detected object;

This point is later used to detect whether the detected animal is located inside or outside the protected crop-field boundary.

Object from the detector use following tasks together to perform opportunity gives: *classification; localization; objects count; virtual border with compare; the object observation.*

Each in the video frame detection results separately is considered (Table 4). Therefore, of objects time according to movement detection for many with object observation algorithm necessary. This for the purpose ByteTrack or to him/her equivalent from the algorithm use possible [11]. Each being observed to the object separately identifier attached. This stage especially cattle, sheep and in goats important because one to the image looking at of the animal crop to the field entering or from it moving away detection difficult [12-13].

Table 4. Proposal being done answer strategy

Object	Low danger	Medium danger	High danger
Cattle	Note to grow	To the farmer message	Message + short audio / light signal
Sheep	Note to grow and counting	Message	Group danger message + deterrent
Goat	Note to grow	Message	Short audio / light deterrent
Rat	Repetition record to do	Activity map update	Local pest control about message
Bird	Note to grow	Stable in a group if message	Variable acoustic /visual deterrent

Each animal type for strict universal “optimal frequency” designation scientific in terms of right not because of the animal to the sound reaction distance, intensity, environment, foreground experience and getting used to with depends [14]. In rat’s ultrasound universal basic protection tool as acceptance to do recommendation This is not possible. instead of repetitive detections based on active zones identified, local pests’ control to do measures planning to the goal according to. In birds and answer one bird to be detected not, maybe in a group number and in the area stay to the duration justification need. The proposed system uses an event-driven communication model. Instead of continuously transmitting the entire video stream to the cloud server, the edge device processes the captured frames locally and generates a compact event messages only when relevant intrusion is detected. This approach reduces unnecessary GSM/4G data traffic and improves the efficiency of the communication channel [14].

IV. EXPERIMENTAL RESULTS

To evaluate the effectiveness of the proposed intelligent agricultural field protection system, a set of images consisting of five main classes: cattle, sheep, goats, rats and birds was used. The experimental set consisted of a total of 7850 images and 14050 detected objects, including images taken in both day and night conditions.

During the experiment, the stages of object detection, multi-object tracking, virtual boundary intrusion detection and risk assessment were performed sequentially. The model effectiveness was evaluated based on accuracy, completeness, F1-criterion, object tracking accuracy and the number of false alarms. The proposed object detection model was used to obtain experimental results for five main object classes in agricultural fields. The detection results showed that large objects, especially cattle, are detected with high accuracy. This is mainly due to the large pixel area they occupy in the image. However, the detection complexity increases for small objects such as rats and birds, as they occupy a small pixel area and are often found in complex background conditions:

$$P_i = \frac{N_i}{N_{total}} \times 100 \tag{8}$$

Distribution by images represented in Table 5.

Table 5. Distribution of the Animal Dataset by classes

Class	Number of Images	Percentages (%)
Cattle	1450	18.47
Sheep	1680	21.40
Goat	1520	19.3
Rat	1380	17.58
Bird	1820	23.18

Total	7850	100

where the total number of images - N is 7850.

Distribution by objects represented in Table 6.

Table 6. Distribution of the Animal Objects by classes

Class	Number of Images	Percentages (%)
Cattle	1820	12.95
Sheep	3560	25.34
Goat	2410	17.15
Rat	1980	14.09
Bird	4280	30.46
Total	14050	100

The distribution of the experimental dataset by lighting conditions was analyzed. Out of a total of 7850 images, 5140 (65.48%) were daytime images, and 2710 (34.52%) were nighttime or low-light images (Figure 3).

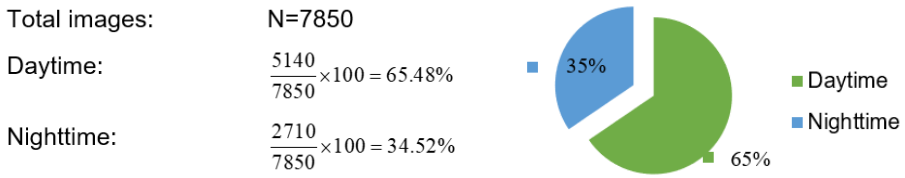


Figure 3. shows the percentage distribution of daytime and night images in the experimental dataset

The results show that the dataset has a high proportion of daytime images, accounting for about two-thirds of the total data. The main reason for this is that during daytime, there is sufficient natural light, which allows for high-quality images to be obtained for object detection. At the same time, the inclusion of 34.52% of nighttime images allows us to evaluate the system's ability to work in low-light conditions. These images are especially important for detecting objects with high nighttime activity, such as rats. The sufficient presence of night cases in the dataset allows us to verify the stable operation of the proposed computer vision model not only in daytime, but also in complex lighting conditions. As a result, the model will be able to adapt to different time conditions in real agricultural fields.

V. DISCUSSION

Offer being done system the object detection with intrusion evaluation from each other separation with traditional monitoring from systems difference does. Cattle large object happened because of in the picture rat and to the birds relatively more pixel the area occupies. This because of them detection relatively easy to be expected. However, plants, watering facilities or other animals body one part block to put possible [14]. Light conditions and animal of the situation. The change also affects the model accuracy. impact does.

Rats detection offer being done in the system the most complicated from tasks one of them. Cattle detection for suitable was camera location rat for enough accuracy failure to provide possible. Therefore, rat activity high in the regions lower to the height installed special camera or thermal from sensors use to the goal This is one universal sensor configuration. All five class for one kind at the level effective that it is not shows. Bird monitoring is also technical and ecological in terms of complicated. They in the picture small, fast moving and many numerical to be possible. From this except for all birds to the field damage does not deliver. Therefore originally from the " bird " class general operational monitoring category as use, later and enough information when gathered, local harmful bird types separately to classes separation to the goal according to.

Offer done danger model of the system important in terms of Model reliability is one of high to be of the event danger level high. For example, field outside detected cattle. The confidence for is 0.98. possible, but this automatic accordingly high dangerous event not to be counted. On the contrary, a how many minute during field inside remaining sheep group much high to danger has to be possible.

Incidental communication strategy of the system practical efficiency increases. Continuously video via GSM/4G send network the load and energy spending increases. On the Edge device object detected, only

important semantic event information to be sent edge village in the regions from the network further effective use opportunity gives.

Edge computing system It also increases the stability of GSM/4G connection. Temporarily interrupted remaining under the circumstances local device objects to detect continue to represent and events local in memory save possible. Contact After recovery, the data with a central server synchronized.

Offer being done each in the system animal for strict frequency. The acoustic signal is not attached. Animals acoustic to the effect reaction distance, signal intensity, environment, age, previous experience and repetitive to the effect to get used to the level It depends. Therefore, acoustic or visual deterrent system main scientific result not, maybe danger to the level looking at controllable assistant tool as is considered. Control to be done field experiences until it is transferred harvest of losses known percent decreased scientific result as show to the goal appropriate it's not. Offer being done approach one row It also has limitations. *First,* the efficiency of the final model local dataset size and diversity strong. *Secondly*, the night rat monitoring for special camera required. *Thirdly*, birds class in the future biological types according to separation need to be. *Fourth*, the big sheep and goat in groups of objects each other barrier counting accuracy reduce. *Fifth*, the risk model weight coefficients experimental accordingly calibration necessary. *Finally*, deterrent effectiveness object detection from quality separately experience through to be checked necessary.

VI. CONCLUSION

This in research computer view, Internet of Things, edge / cloudy calculation and GSM/4G communication technologies-based field crop fields intellectual monitoring to do and protection to do system offer was done.

System five targeted class - cattle, sheep, goat, rat and the birds to detect intended. Traditional movement detection based from systems different accordingly, proposal done in approach one step by step object detector using object type and his/her spatial coordinates is detected. Many with object observation algorithm consecutively in video footage object identifiers saves, virtual field border and of the object really crop to the field entered or his/her outside moving detection opportunity gives. Detected object for to class related danger level, field inside entrance depth, movement direction, objects number, in the field stay duration of the event repetition frequency and model from reliability organization found many factorial danger model offer.

Five class for differential management strategy was formed.

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