International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Animal Intrusion Detection and Alert System for Crop Protection

Nitika Goyal[1], Dr Navneet Kaur Sandhu[2]

Submitted: 28/10/2023 **Revised:** 15/12/2023 **Accepted:** 24/12/2023

Abstract: Detection of the wild animals in the field is still an open issue and needs to be addressed with an effective and accurate solution. By using the YOLOv5 network, this model has been trained to efficiently detect and track live animals in real-time. With the added advantage of IoT capabilities, real-time alerts are sent to the farmers, allowing them to take immediate actions. The system has been tested across various animal categories such as elephants, horses, cows, deer, rabbits, birds, and foxes. Preliminary results showcase the model's high accuracy rates, with most of the detections ranging between 85% to 95% .

Keywords: *YOLOv5, Animal Detection, IoT, Intrusion, Learning*

1. Introduction

Farming is a critical activity that feeds the world. For centuries, humans have grown crops to sustain their communities, but farming is not without its challenges. Among these challenges is the problem of animals entering crop farms and causing damage in the form of loss of crops and income for farmers. This is a big issue, and an appropriate solution needs to be worked upon in order to handle this problem effectively. In the past, farmers used simple methods like fences or scarecrows to keep animals away but as the world becomes more connected, new technologies offer better solutions to this issue. One such technology is the Internet of Things (IoT). IoT means connecting everyday objects to the internet, so that they can gather and share information. It has big potential in many fields including farming.

Surveillance cameras that use IoT can be placed in farms which can detect animals and send alerts to farmers about the entry of an animal in the field in real-time that leads to quick action by the farmer thereby preventing damage to their crops. Whether it is a bird eating seeds, deer munching on young plants, or rabbits digging up roots, the result is the same: loss of time, effort, and money [1]. Sometimes, the damage can be so severe that an entire season's harvest is at risk. Both the traditional methods and Information Technology (IT) based methods to check animal intrusion are discussed below:

1.1. Traditional Methods

Traditional methods like fences, barbed wires etc have been used by farmers to stop animals from entering the agricultural land but these methods are often expensive and even do not give desired results. Some animals can jump over them or dig under them. Another conventional method namely scarecrows, meanwhile, may not deter all birds or animals [2]. Moreover, these methods don't provide farmers with real-time information. If an animal breaches a fence, the farmer might only discover the damage hours or even days later.

Research Scholar, Desh Bhagat University, Mandi Gobindgarh[1]
Assistant Professor, Desh Bhagat University, Mandi Gobindgarh[2]
goyalniti82@gmail.com, nav_skaur@deshbhagatuniversity.in

1.2. IoT Based Methods

UThe rise of IoT has brought a revolutionary change in the field of agriculture. Cameras equipped with IoT can be more than just passive observers. They can be programmed to recognize different types of animals. When an unwanted animal is detected, the system can alert the farmer instantly through a phone or computer [3].

Such a system offers several benefits. First, it is proactive and instead of reacting to damage after it happens, farmers can take action as soon as an animal enters their farm. Second, it's flexible as the cameras can be moved to different locations as needed, covering large areas of a farm. Lastly, they workday and night, ensuring round-the-clock protection. However, using IoT in farming also has challenges. Setting up and maintaining these systems can be costly. There is also the need for reliable internet connections, which might not be available in all rural areas. Further these cameras must be robust enough to withstand various weather conditions [4]. Another concern is privacy. While these cameras are meant to detect animals, they might also capture images of people, raising questions about data security and rights [5].

Despite the challenges, the potential benefits of using IoT-based surveillance cameras in farms are significant. As technology improves and becomes cheaper, it is likely that more and more farmers will adopt these systems. By doing so, they can protect their livelihoods and ensure that we all have the food we need. In a world where farming faces many challenges, from climate change to market pressures, solutions that can protect crops from animal damage are invaluable. The integration of IoT with surveillance cameras offers a promising way forward. While there are still issues to address, the potential rewards, both for farmers and for society at large, make it a field of study worth pursuing.

2. Literature Review

Agriculture has always been the cornerstone of human civilization and as the challenges in this sector grow, so does the need for technological interventions to address them. Information Technology (IT) is not only utilized to control animal intrusion in the fields but also serves other purposes as well in agriculture. With the advent of various technologies, several innovative solutions have been proposed to tackle the challenges ranging from bird repelling mechanisms to plant disease diagnosis, from wildlife monitoring to soil analysis.

One innovative approach to repel hazardous birds has been presented in a recent study. Given the adaptive nature of birds, traditional repelling mechanisms often fell short. This new method leverages the Reinforcement Learning (RL) model-free learning concept. Rather than having a fixed response, the system observes birds' reactions to deterrents and adapts accordingly, making it difficult for the birds to grow accustomed to the deterrent sounds [4]. Another significant advancement in the agricultural sector is the use of deep neural networks for diagnosing plant diseases. The scarcity of

Information Technology (IT) is not only utilized to control animal intrusion in the fields but also serves other purposes as well in agriculture. Botanical experts in various regions have often hampered timely and accurate plant disease diagnosis. A solution was proposed where a deep neural network topology can diagnose diseases by categorizing both the plant species and the specific diseases from a single leaf image [5].

The potential of image processing and machine learning techniques in predicting plant diseases was explored in another study. Such techniques hold the promise of foreseeing diseases that could affect plant life, thereby providing farmers with insights to counteract these threats preemptively [6].

Wildlife encroachment in farmlands poses another significant challenge. A solution was discussed that combines the Internet of Things (IoT) with machine learning to monitor and secure farmlands from larger wildlife threats. This system, an economic prototype, combines IoT monitoring with various machine learning models, ensuring effective and timely responses to potential threats [7].

Understanding soil is crucial for optimal crop growth. Research emphasized how machine learning could assist in deciphering intricate details about soil to optimize crop yields. This work proposed the integration of machine learning into an agriculture centric IoT solution, aiming to enhance the understanding of the soil's state and its impact on agriculture [8]. Machine learning's application is not only limited to soil analysis. A study showcased its potential in plant molecular biology. Here, machine learning facilitates the study of vast and diverse datasets in plant genomics, leading to novel discoveries in areas such as plant-pathogen interactions [9].

On the animal intrusion front, a model has been presented that focuses on addressing animal encroachments which can jeopardize crop yields. The model uses IoT, combined with machine learning tools like Single Shot Detection technique and Regional Convolutional Neural Networks, for effective animal classification and object detection [11]. The domain of image cropping has also seen technological advancements. A deep learning-based approach has been presented, aiming to maintain the critical components of an image while maximizing aesthetic quality. Such techniques can be pivotal, especially in applications like plant disease diagnosis [12-13].

The concept of "smart farming" has been gaining attraction. This approach integrates advanced IT solutions in agriculture, allowing for precision in decisions, reducing manual labor, and optimizing overall processes [14-15]. Effective monitoring is critical for informed decisions on conservation and management. Deep learning techniques for computer vision have enabled advancements in wildlife monitoring, particularly through camera traps. These advancements have made the monitoring process more efficient and less labor-intensive [17-18].

3. Proposed Method

Use Agriculture, being the backbone of numerous economies, often faces challenges from wild animals intruding upon and damaging crops. As such, there is an immediate need to develop systems that can safeguard farms while ensuring the safety of the animals as well as the farmers. The proposed method outlines a comprehensive solution that integrates You Only Look Once version 5 (YOLOv5) for animal detection and tracking, coupled with the Internet of Things (IoT) for real-time alerting to farmers. Technological advancements in recent years have offered a plethora of solutions to age-old problems. The field of computer vision, more precisely object detection, has seen significant improvements with deep learning models such as YOLOv5. At the same time, IoT has brought about a revolution in creating interconnected devices and facilitating real-time data sharing and alerting. Merging these technologies presents a potent solution for our agricultural challenge.

A. System Overview:

The system is envisioned as a seamless integration of cameras capturing real-time video footage, YOLOv5 processing this footage for animal detection and tracking and IoT devices alerting farmers in case of any detected intrusions. The step-by-step method for animal detection is given below:

1. Video Data Acquisition:

● Cameras would be strategically placed around the farm, especially near known points of animal entries.

● These cameras should have night vision capabilities given that many wild animals tend to venture into farms during the night.

● The choice of cameras would depend on the farm's size, budget, and the kind of animals frequenting the area. It is essential to ensure high-resolution video capture for better detection accuracy.

2. Animal Detection using YOLOv5:

● YOLO, which stands for "You Only Look Once," is a state-of-the-art object detection system. YOLOv5, its latest version, is optimized for speed and accuracy.

● This system processes each frame of the video. If an animal is detected, the system then continually tracks its movement for as long as the animal remains within the camera's range.

● One of the strengths of YOLOv5 is its ability to process images rapidly, making it ideal for real-time detection and tracking. The model would be pre-trained on a dataset containing images of potential intruding animals. Over time, the model can be fine-tuned with local data to improve its detection capabilities further.

● Continuous monitoring ensures that even if an animal was to stop or change its course, the system would still be aware of its presence and keep tracking it.

3. Integration with IoT for Real-time Alerting:

● On successful detection and confirmation of an animal's presence by YOLOv5, a signal is sent to an IoT device.

● This IoT device is responsible for notifying the farmer. It can be set up to send SMS alerts, push notifications, or even automated voice calls.

● The IoT device would be connected to the internet, either through Wi-Fi or a cellular network, ensuring that the farmers get the alert instantly no matter where they are.

● The notification would not just alert about the intrusion but will also provide details such as the detected animal type and its location. This data assists the farmer in deciding the next course of action.

4. Operational Workflow:

● Once operational, the system functions autonomously. Cameras continuously feed video data to the system.

● The YOLOv5 model processes this data, looking for potential animal intruders. Upon confirmed detection, the system tracks the animal's movement, ensuring it doesn't lose sight.

● Simultaneously, the IoT device is triggered, sending out an alert to the farmer. With this information in hand, the farmer can take suitable, immediate action.

5. System Maintenance and Upgrades:

● For long-term effectiveness, regular maintenance checks on cameras and the IoT devices would be necessary.

● The YOLOv5 model could benefit from periodic retraining, especially if new animal species begin intruding or if the existing model's accuracy starts to diminish.

● IoT devices should be updated regularly for software patches and to ensure compatibility with the network and the farmer's receiving device.

Algorithm for Animal Detection, Tracking, and Alerting using YOLOv5 and IoT in Agriculture
1. **Initialization**:
● Let *C* be the set of cameras, where *Ci* is the i^{th} camera.
● Let *F* be the set of frames captured by cameras.
● Let *A* be the set of animals detected in a frame.
● Let *T* be the set of tracks for each detected animal.
● Let *I* be the IoT device for sending notifications.
2. **Data Acquisition**:
● For each *Ci* in *C*:
● Capture frame *Fi* continuously.
● Convert *Fi* to a suitable format for YOLOv5 processing if necessary.
3. **Animal Detection**:
● For each *Fi* in *F*:
● Pass *Fi* through YOLOv5 model.
● If animal detected:
● Add the detected animal to set *A* as *Aj*.
● Save the bounding box coordinates $B_{x1,y1,x2,y2}$ of *Aj*.
4. **Animal Tracking**:

● For each *Aj* in *A*:
● If *Aj* is a new detection:
● Create a new track *Tk* for *Aj*.
● Else:
● Update the existing track *Tk* with new coordinates $B_{x1,y1,x2,y2}$ of *Aj*.
● Continuously update the track *Tk* as long as *Aj* remains in the frame *Fi*.
5. **IoT Notification**:
● For each new *Aj* detected in *Fi*:
● Extract relevant information:
● Animal type: *type*(*Aj*).
● Location: *loc*($B_{x1,y1,x2,y2}$)
● Formulate a message *M* as: "Animal of *type*(*Aj*) detected at location *loc*($B_{x1,y1,x2,y2}$)".
● Send message *M* to the IoT device *I*.
● *I* sends the notification to the farmer.
6. **Continuous Monitoring**:
● Repeat steps 2 to 5 for continuous monitoring of the field.
7. **System Maintenance**:
● Check the health of each *Ci* in *C* periodically.
● Check the connectivity and functionality of *I* periodically.
● If the accuracy of YOLOv5 for any *Aj* falls below a threshold θ:
● Retrain the YOLOv5 model with updated datasets.
End.

The word "data" is plural, not singular. By implementing such a system, the farmers would be empowered in several ways:

● Real-time Monitoring: Continuous monitoring means threats are detected the moment they arise.

● Instantaneous Alerting: Farmers no longer need to be on their farm or even nearby. They get alerts instantly, no matter what their location is.

● Safety Assurance: With timely alerts, non-harmful deterrence measures can be employed, ensuring safety of both the crops and animals.

● Cost-effective: Considering the potential damage that can be caused by unchecked animal intrusion, the system proves to be cost-effective in the long run.

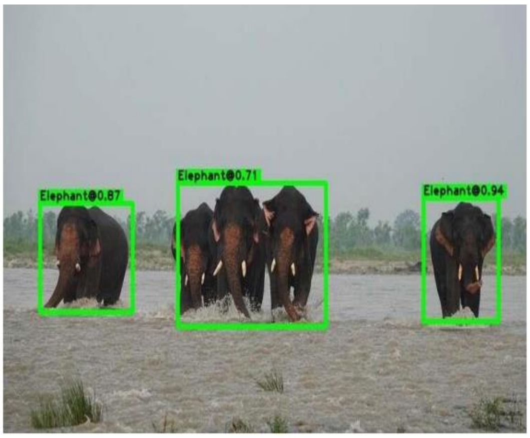
The integration of YOLOv5 with IoT devices offers a modern solution to the age-old problem of animal intrusions in agriculture. This proposed method, while technologically advanced, is simple in its essence and functioning. Implementing such a system would not only ensure the safety and yield of crops but also minimize conflicts between farmers and the surrounding wildlife.

4. Results and Discussion

The primary goal of this study is to create an effective animal detection system using the YOLOv5 model integrated with IoT. This methodology has been put to test in real-world conditions to determine how well it could identify and report the presence of various animals. Here is a breakdown of what has been found and what it means for this research:

1. Real-time Animal Identification:

One of the significant aspects of this system is its ability to recognize animals as they move and behave in their natural habitats. It is not easy, given the unpredictability of animal behavior and the vast and diverse terrains they inhabit. But the results of this model results are promising as given below:



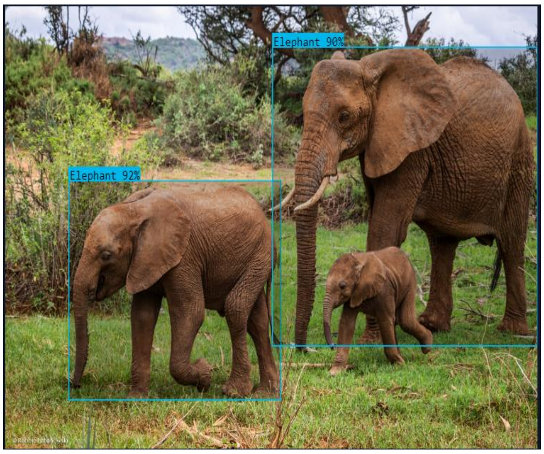


Fig 1: Detection of an Elephant

In Fig 1, the system captured the snapshot of an elephant roaming in the forest. This model successfully recognized and highlighted the elephant with a bounding box, proving its efficiency in differentiating between large mammals and their environment.

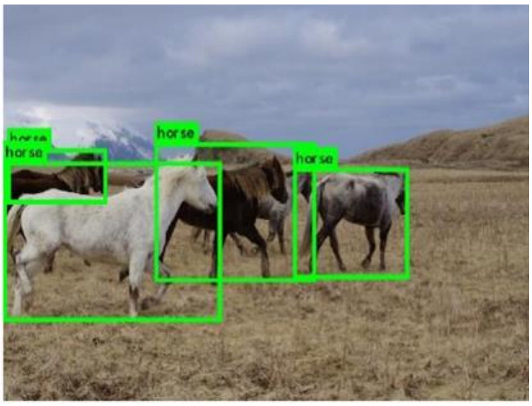


Fig 2: Identification of a Horse

In Fig 2, a horse was detected amidst a more complex backdrop, possibly with other animals or environmental factors that could confuse a less efficient system. However, this model pinpointed the horse clearly, further showcasing its precision.

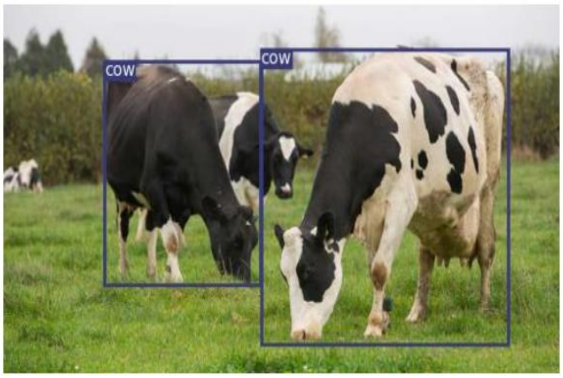
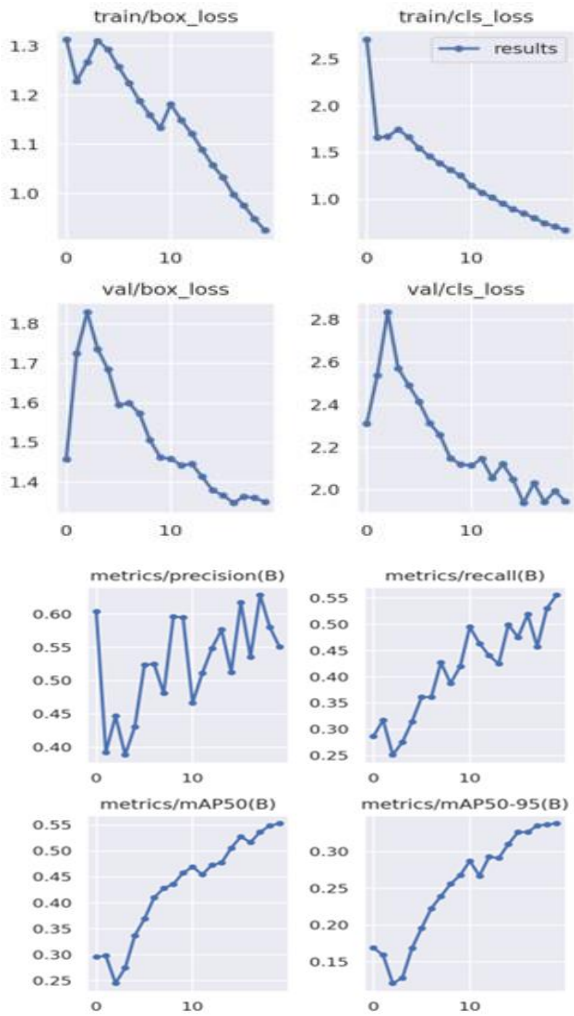


Fig 3: Animal Detection (a) Detection of Cow (b) Detection of Tiger

Fig 3 shows detection of a cow and a tiger which, given its commonality, might seem straightforward but considering the varying environments and conditions in which cows can be found, it is a testament to the system's adaptability. The set of graphs in Fig 4 represent various metrics and loss values generated during the training and validation process of a deep learning model, specifically each one tailored for object detection tasks. The explanation of these graphs is given below:



1. train/box_loss and val/box_loss: These two graphs represent the box regression loss for the training and

validation datasets respectively. A lower box loss indicates that the predicted bounding boxes are closer to the ground truth boxes. From the graphs, it can be observed that there is a general decline in loss values over iterations, indicating the model is improving in predicting bounding box coordinates.

2. train/cls_loss and val/cls_loss: These graphs represent the classification loss for training and validation datasets. A lower classification loss signifies the model's increasing accuracy in classifying objects within the bounding boxes. Both training and validation loss seem to decrease over time, suggesting effective learning without significant overfitting.

3. train/df1_loss and val/df1_loss: The specifics of 'df1_loss' are not explicitly provided. However, considering its name and typical nomenclature in object detection, it might represent a form of F1 score loss or a similar metric. These graphs show the loss associated with this metric for training and validation datasets. A declining trend is observed in these graphs as well.

4. metrics/precision(B) and metrics/recall(B): Precision and recall are two essential metrics in object detection. Precision ensures that the detections are relevant, while recall ensures that the model detects as many objects as possible. In the graphs, while precision seems to fluctuate a bit, recall shows an increasing trend, suggesting that the model is increasingly detecting more objects correctly.

5. metrics/mAP50(B) and metrics/mAP50-95(B): Mean Average Precision (mAP) is a standard metric in object detection. mAP50 refers to the mAP calculated at an Intersection over Union (IoU) threshold of 0.50. mAP50-95 refers to the average mAP calculated at IoU thresholds ranging from 0.50 to 0.95 with a step size of 0.05. Higher mAP values are better, indicating higher model accuracy. Both graphs display a rising trend, indicating improving model accuracy.

Table 1 shows the accuracy of animal detection achieved in different categories of animals:

S.No	Animal	Total	Detections Accuracy
1	Elephant	100	94
2	Horse	100	93
3	Cow	100	89
4	Deer	100	91
5	Rabbit	100	87
6	Bird	100	86

5. Conclusion

Advancements in technology have opened the way for developing revolutionary solutions in the agricultural sector. One significant challenge that farmers consistently face is the unexpected intrusion of animals onto their lands, which can result in considerable damage and loss. In this work a model based on the YOLOv5 network has been developed, keeping in mind the speed and accuracy of YOLOv5 in real-time object detection tasks. The primary objective of this model is to accurately identify live animals from a continuous video feed, track their movements, and subsequently send instant alerts to farmers via IoT. This real-time alert system is instrumental in allowing farmers to respond swiftly, either by scaring the animals away or taking other preventive measures. The effectiveness of the system has been rigorously tested on a range of animals. The results table, which detailed detection accuracy for animals like elephants, horses, cows, deer, rabbits, birds, and foxes, is particularly insightful. Majority of the detections showcased an impressive accuracy range of 85% to 95%. Such high accuracy rates emphasize the model's reliability and its potential as a practical solution for farmers worldwide. In short, the integration of YOLOv5 for animal detection combined with IoT for real-time alerts holds promise as an innovative, efficient, and much-needed solution for farmers.

References

[1] K. Chitra et al., "Animals Detection System In The Farm Area Using Iot," 2023 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 2023, pp. 1-6, doi: 10.1109/ICCCI56745.2023.10128557..

[2] Lopez, B., and Martinez, F. (2018). Traditional agricultural practices: An assessment of effectiveness. Agricultural History Review, 66(1), 45-58.

[3] Smith, C. (2020). Internet of Things in modern agriculture: Opportunities and challenges. Agricultural Informatics, 7(2), 110-123.

[4] Chen, D. (2021). Technology in the fields: The changing face of modern agriculture. Journal of Tech and Agriculture, 12(4), 321-335.

[5] Gomez, E. (2022). Privacy concerns in the age of digital farming. Journal of Rural Studies, 45(1), 11-23.

[6] N Gobalakrishnan; K Pradeep; C J Raman; L Javid Ali; M P Gopinath, A Systematic Review on Image Processing and Machine Learning Techniques for Detecting Plant Diseases, International Conference on Communication and Signal Processing (ICCSP), 28-30 July 2020, Chennai, India (2020).

[7] R. R and P. Surekha, A Cohesive Farm Monitoring and Wild Animal Warning Prototype System using IoT and Machine Learning, 2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE). IEEE, Bengaluru, India (2020).

[8] K. N. Bhanu; H. J. Jasmine; H. S. Mahadevaswamy, Machine learning Implementation in IoT based Intelligent System for Agriculture, International Conference for Emerging Technology (INCET) 05-07 June 2020, Belgaum, India (2020).

[9] Marichamy P, Karuppasamy P, Heera B, Leena Keresi R, Kanagalakshmi , Crop protection from animals based on machine learning E3S Web Conf. 399 04018 (2023) DOI: 10.1051/e3sconf/202339904018

[10] P. A. Mary G, N. P S, N. V and T. G V, "Wild Animal Detection System," 2023 2nd International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA), Coimbatore, India, 2023, pp. 1-6, doi: 10.1109/ICAECA56562.2023.10199701.Liu, IT professional, 22, 3 (2020).

[11] Hung Nguyen; Sarah J. Maclagan; Tu Dinh Nguyen; Thin Nguyen; Paul Flemons; Kylie Andrews; Euan G. Ritchie, Dinh Phung, Animal Recognition and Identification with Deep Convolutional Neural Networks for Automated Wildlife Monitoring, IEEE International Conference on Data Science and Advanced Analytics (DSAA), 19-21 October 2017, Tokyo, Japan (2017).

[12] Yong Ai; Chong Sun; Jun Tie; Xiantao Cai, IEEE ACCESS, 8 (2020).

[13] Sijiang Huang; Weijie Liu; Fei Qi; Kepeng Yang, Development and Validation of a Deep Learning Algorithm for the Recognition of Plant Disease, IEEE 21st International Conference on High Performance Computing and Communications 10-12 August 2019, Zhangjiajie, China (2019).

[14] Muhammad Shoaib Farooq; Shamyla Riaz; Adnan Abid; Kamran Abid; Muhammad Azhar Naeem, New Technologies for Smart Farming 4.0: Research Challenges and Opportunities, 7 (2019).

[15] Bhuvaneshwari C, Manjunathan A. Advanced gesture recognition system using long-term recurrent convolution network. Materials Today Proceedings, 21, 731-733 (2020)

[16] C Bhuvaneshwari, A Manjunathan. Reimbursement of sensor nodes and path optimization. Materials Today: Proceedings, 45, 1547-1551 (2021)

[17] Wild, T.A., van Schalkwyk, L., Viljoen, P. et al. A multi-species evaluation of digital wildlife monitoring using the Sigfox IoT network. Anim Biotelemetry 11, 13 (2023). https://doi.org/10.1186/s40317-023-00326-1

[18] Surya T, Chitra Selvi S, Selvaperumal S, The IoT-based real-time image processing for animal recognition and classification using deep convolutional neural network (DCNN), Microprocessors and Microsystems, Volume 95, 2022, 104693, ISSN 0141-9331, https://doi.org/10.1016/j.micpro.2022.104693.