Crop protection from animals based on machine learning

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Abstract. This paper will discuss the present level of research and development on human-wildlife conflicts, there are bad interactions between humans and wild animals that are bad for both the resources of the human population as well as the ecosystems of wildlife. Animal detection has an impact on both human food security and animal welfare because it arises from the conflict between humans and wildlife over natural resources. As the population has grown and many communities' land use patterns have changed, these disputes have become more prevalent in recent years. The Mobile Net SSD type is used in this automatic intrusion and deterrent system for enhanced performance. When a dangerous animal is discovered, the system emits an alarm sound and notifies the relevant authorities, alerting them to the discovery. It is more human- friendly due to the quick detection process, and it is more animal-friendly due to the gentle repulsive process.

1 INTRODUCTION

The increased conversion of wild habitats into cultivated fields forces migratory behavior among wild animal populations. This eventually encouraged wildlife to enter human environments in search of food and shelter, resulting in Human-Wildlife conflicts. One of the conflicts that alienate people and wildlife the most is crop raiding. Understanding ecology requires research on wild animals in their natural environments. The rapid, inventive, and profound changes in the Earth's ecosystems are a result of the tremendous rise in human population and the expansion of the quest of economic development. Natural life has changed in terms of quantity, habitat, and behavior as a result of human activities having an increasing impact on the surface of the globe. Damage from animal assaults is one of the main dangers to crop production loss. Humans in turn adopt some preventative actions to fend off these losses. More unfortunately, many wild animals have almost completely disappeared After leaving the earth, some species have relocated to new areas where they can still have an impact on both people and natural resources. Studies demonstrate that most wild animal deaths go unreported or neglected for months, demonstrating the forest department's general negligence. The government conducted multiple campaigns to remove illegal fences to reduce the overall fatality rate, but incidents still happened and to some part go undetected. This demonstrates the equal sharing of losses between people and animals. If the presence of these wild creatures can be made known in advance, then these conflicts and fatality rates are expected to decrease. With the advancement of technology, numerous systems for deterring wild animals were developed using IoT technologies. The most common use for a subset of deep neural networks is convolutional neural networks. (CNN),is the analysis of visual images. A class of algorithms known as deep neural networks has set new benchmarks for accuracy in some crucial jobs. Comparatively speaking to traditional image classification methods, CNN uses a lot less pre-processing.

A number of factors, such as agricultural diseases and insect pests, seriously jeopardize agricultural productivity. The economic losses brought on by pests can be effectively decreased by early identification and detection of pests. In this study, crop diseases are automatically identified using convolution neural networks. The open data set of the 2018 AI Challenger Competition was used to generate the data collection and it contains 27 photos of illnesses affecting 10 different crops [1]. An in-depth analysis of machine learning applications in precision agriculture SHARMA, ABHINAV 2021 IEEE. Every nation's economic development depends heavily on agriculture. The current population has a high need for food, which makes meeting that demands a difficult undertaking due to population growth, frequent climatic changes, and a lack of resources. As a cutting-edge technology to address contemporary issues in agricultural sustainability, precision agriculture, often known as smart farming, has arisen. Machine learning is the engine that propels this innovative technology [2]. Systems and technology have proven the ability to process information utilizing hyperspectral and multispectral data. Supplying farmers and crop managers having vital information on the factors affecting crop health and growth, is valuable in enhancing agricultural practices and output. These technologies are heavily utilized in agricultural applications, including crop management and crop yield projections, agricultural disease detection, and crop health

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surveillance of soil, water, and land use. Using the use of hyperspectral information sensing, the whole electromagnetic spectrum of a scene under observation can be covered by several hundred spectral bands in a single acquisition.[3]

Proposed in the March 2021 issue of the CHEOL WON LEE International Journal of "Geo-Information" is an anti-adaptive hazardous bird repelling technique based on reinforcement learning. To guard against crop damage from invasive birds, several repelling strategies have been investigated. Dangerous birds still cause damage to the orchard even though they have evolved a repelling mechanism that matches their biological makeup. This research proposes an approach Effectively addressing bird adaptation issues a technique known as Protection Against Negative Birds Repulsion (AHBR), which applies the Reinforcement Learning (RL) methodology's model-free learning concept. The AHBR method uses a strategy that entails observing the response of the bird to the dangerous noises that are there and playing them in patterns that make it challenging for the bird to adjust using the RL approach [4]. Development and Validation IEEE proposed the Sijiang Huang Conference in 2019. The basis for agricultural development is healthy crops. Due to a shortage of qualified botanical experts in some regions, it might be challenging to appropriately diagnose plant diseases when planting. In this research, we provide a novel deep mental network topology that allows for complete plant diagnosis of diseases by precisely categorizing plant species and diseases from a single plant leaf image. A leaf segmentation model and a model for categorizing plant diseases make up our suggested model [5]. For the year 2020, N Gobalakrishnan of the IEEE proposed a thorough investigation of image processing and machine learning methods for identifying plant diseases. Techniques that can predict the types of diseases that would afflict a plant's life would be very helpful to farmers. In a carefully executed investigation, numerous image-based plant leaf diseases were explored, and this article provides light on such techniques. These diseases can harm any part of the plant and can result in severe suffering. These illnesses hurt Massive losses result from decreased productivity and increased financial losses in the agricultural sector. Although technology has permeated every part of modern life, the agriculture industry has not yet been completely affected [6].

Machine learning and the Internet of Things are used in a coordinated wild animal monitoring and farming alert innovative system. For 2020, the Raksha R Conference and IEEE are scheduled.AI and the Internet of Things advancements have been particularly helpful in addressing common issues in the agricultural sector. It has become essential to have a strong To keep animals like elephants away from these farms, a monitoring and surveillance system is in place. This study uses these two technologies to present a unified, economic prototype system. Along with an IoT- based monitoring system, a study of KNN, Logistic Regression, and SVM, among other machine learning models is also provided. A recommendation for the model that is most accurate for the monitoring system is given after an evaluation of the relevant parameters [7]. In 2020 proposal by Bhanu K. N. IEEE to integrate machine learning into an agriculture-focused intelligent IoT solution. Everyday life has changed as a result of the invention of the IOT. The majority of countries place a high priority on agriculture, and it needs to develop "Smart" practices. The absence of understanding regarding soil is a key inference. There are numerous different varieties of soil, and each one has unique features. A detailed understanding of the state of the soil can lead to a variety of information about the soil that can be used to improve crop yields. The agriculture industry uses machine learning, a popular technology, to develop precision and find answers to crop production issues. The numerous machine-learning concepts for IoT-based smart agriculture systems are thoroughly examined in this research [8]. In 2019, IEEE Jose Cleydson F submitted a thorough analysis of Current applications of machine learning in plant molecular biology. Molecular biology has seen rapid development in the artificial intelligence field of machine learning (ML).This has made it possible for plant genomics to utilize Big Data principles. The primary difficulties in analyzing large This context describes datasets and novel information extraction at research on biological systems at all levels. In conclusion, ML approaches enable the inference of complicated relationships in various biological systems. The important stages of the evolution of ML (From choosing the data through assessing classification and prediction models) were highlighted as we talked about functional genomics regarding genes that affect pathogens in plants' defenses. Furthermore, we introduced new potent techniques like deep learning and thought about how to use open-source materials inside of an ML framework to progress plant molecular biology [9]. The era of "Big Data" in biology has arrived thanks to the quick developments in high-throughput genomic technology (large datasets). To comprehend the enormous amounts of data, the community of plant scientists must not only develop its infrastructures for concurrent computing and data management that are Big-Data compatible but also look for new analytical paradigms. Machine learning is steadily gaining acceptance in biology because it is for the integrated study of vast, heterogeneous, and unstructured datasets on the Big Data scale, and offers potential computational and analytical solutions. [10]

Animal encroachment substantially jeopardizes crop output while also reducing farmer profitability and endangering food security. The suggested model demonstrates how this problem is being addressed through the Internet of Things with machine learning. All of the components are connected to the Raspberry Pi, which manages the machine algorithm, including the Pi Camera, the ESP8266 Wireless Fidelity module, the Buzzer, and the LED. Tools for machine learning, such the as Single Shot Detection technique and Regional Convolutional Neural Networks are essential for classifying animals and identifying objects in photographs. The results of the tests indicate that the Single Shot Detection technique performs more effectively than the Region-based Convolutional Neural Network approach [11]. IEEE members Jianbing Shen and Wenguan Wang have proposed an Attention and Aesthetics Sensitive Deep Network Solution for Image Cropping for the year 2018. Choosing a cropping window for an input image that keeps the input image's fundamental components while keeping as many of its aesthetic qualities as is practical will be the focus of this article's discussion of the topic of photo cropping. To develop using a deep learning-based approach, we build a brain network with dual branches: one for box prediction of attention (ABP) and the other for aesthetic evaluation. Using the aesthetic evaluation as a basis, the ABP network foresees an attention-grabbing box as the first minimal cropping window and then offers a few further cropping possibilities close by with a minimal knowledge loss that is crucial. The two sub-networks are computationally effective since they are made to share a single full-image convolutional feature map [12-13].

By integrating cutting-edge information technologies, The revolutionary concept of "smart farming" aims to boost agricultural output and efficacy. Farmers are better equipped to monitor every step of the process You use certain remedies chosen by machines with human-like precision thanks to new developments in automation, artificial intelligence, and networking. Researchers in agriculture, engineering, and data science are still working on ways to increase the amount of labor required by the sector. As crucial information sources improve, intelligent farming develops into a learning system that becomes smarter every day [14-15]. Agriculture and Artificial Intelligence (AI) IEEE's Simon Y. Liu May 2020 is the proposed date. Due to issues including the rapidly rising population, shrinking arable land, decreasing ecological resources, unexpected global warming, and changing shopper demands, The paradigm of agricultural production is being pressed into a new direction. Regarding output, operational efficiency, and resistance the new agricultural system needs to be more productive to combat climate change and ensure sustainability for future generations. Artificial intelligence may be used to tackle the challenges offered by this new paradigm (AI). With more than 2000 scientists conducting research on agriculture in more than 90 places across both three and the United States and other countries, the Agricultural Research United States Department of Agriculture Service (ARS) (USDA) is the top organization for agricultural research in the world [16]. Decisions on conservation and management must be supported by effective and trustworthy keeping an eye on wild creatures in their natural habitats. Due to their value and dependability in collecting wildlife data inconspicuously, consistently, and in large volumes, automatic covert cameras, often known as "camera traps," are becoming a more and more common instrument for wildlife monitoring [17]. Unfortunately, The cost, effort, and time required to manually process such a massive amount of pictures and movies taken using camera traps are prohibitive. In this essay, we suggest a framework for building automatic animal detection in the field and an automated system for tracking animals. We accomplish this by making use of recent developments in deep learning techniques for computer vision [18].

2 Proposed methodology

The developed device intends to defend populated areas and agricultural areas from intrusions and attacks by wild animals. An autonomous system that can detect the intrusion of wild animals can drive them away without injury. The stated operations are carried out with the aid of a deep learning technique. An alarm sound is made after a wild animal is discovered to scare it away. To inform the appropriate authorities of the detection, an alert message is also transmitted. Thus, reducing the harmful effects of the conflict and advancing the usage of smart agriculture applications. The system's primary goal is to provide an automated method for detecting and discouraging wild animals in areas where people live and in agricultural fields. The suggested methodology uses IoT and artificial intelligence technologies to protect crops from animal encroachment. To run Raspberry Pi, 12V of alternating electricity is transformed into 5V of direct current using a bridge rectifier circuit and the 7805-voltage regulator. An interface between an ESP8266 and an Arduino board gives the system access to the Firebase cloud. With a Raspberry Pi 4, a machine learning algorithm is executed in Fig.1.

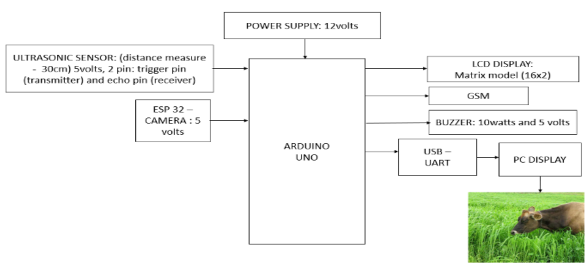

Fig. 1. Intruders entering the field of crops

Next, while running on the Arduino board, the machine learning application analyses the images, producing conclusions as a result. The Arduino utilizes a buzzer to emit sounds at various frequencies when a threat is discovered. The ultrasonic sensor and buzzer are simultaneously activated if the entry is discovered at night to frighten the trespasser from the field. The suggested paradigm is divided into two components: hardware and software. As the brains of the hardware, Python communicates with elements including one that regulates voltage, Pi Camera, an ultrasonic sensor, WiFi, and a buzzer. For the software component of the hardware, Python is used. and machine learning is used to model object recognition and predict animals' computer vision. We approach the photo cropping task more naturally and effectively than earlier artworks, making the following significant contributions: An attention-and-aesthetics combining deep learning approach for photo cropping high efficiency of calculation. Using a deep stoop to treat visual issues normally requires a lot of training data, Therefore, the case of cropping photos, entails a large number of carefully annotated cropping results. To satisfy such a request, however, is challenging. because photo cropping takes a lot of time and, more significantly, is quite subjective because it is impossible to define what constitutes "ground truth" cropping. Consequently, it is challenging and It is essentially impossible to train a network to directly construct a cropping window. By avoiding this issue, we can predict the human gaze and rate the aesthetic quality of photos using rich data that is much easier to obtain. It is significant to note that, despite not using cropping results in training, our technique has proven to have great performance on the cropping problem in our extensive trials.

2.1Yolo architecture

YOLO is Convolutional Neural Network (CNN) that excels at swiftly recognizing objects. Incoming images can be recognized as ordered arrays of data by classifier-based systems called CNNs (view the photo underneath). YOLO's benefit is that it's faster as compared to other networks yet maintaining precision in a model's whole context affects its predictions since it allows the model to view the entire image while being tested. YOLO and other convolutional neural network approach "rank" regions based on how much they resemble predefined classes. For the class to which they are most closely related, areas with high scores are reported as positive detections. For instance, YOLO can be used to identify various vehicle types in a live traffic feed depending on which portions of the video perform well with particular classes of targets. The YOLO collection of deep learning models was created for quick object recognition. YOLO has three main variations: Yolo versions 1, 2, and 3. A general architecture was suggested in the first iteration, and the second, the bounding box proposal was enhanced utilizing pre-set anchor boxes; and in the third, the model architecture and training method were improved in Fig.2.

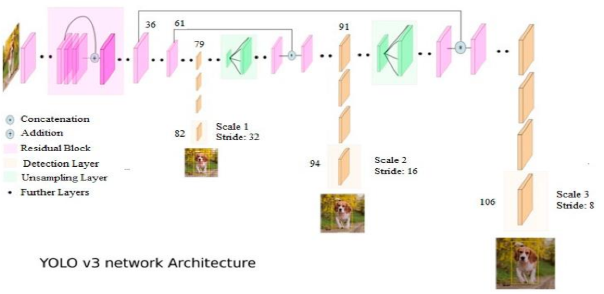

Fig. 2. YOLO vs Network Architecture

The foundation of this approach is the hypothesis an individual neural network can accurately forecast class probabilities and bounding boxes from a collection of all- inclusive images in a single assessment. One network underpins the whole detection process, allowing for ongoing adjustment to detection performance. Darknet version YOLO v3 makes use of a 53-layer network that was initially trained on Imagenet. 53 more layers are added to the underlying 106-fully convolutional architecture with layers to make it more suitable for the YOLO v3 detection challenge. Utilizing 1 x 1 detection kernels and feature maps of three different sizes located at three distinct locations around the network, YOLO v3 recognizes objects. The detection kernel is formed as 1 x 1 x (B x (5 + CB is the largest bounding box that a feature map cell can predict, C is the number of bounding box characteristics, and 5 is the maximum number of classes. Class predictions and object confidence are assessed Logistic regression is utilized, whereas Binary cross-entropy is used by YOLO v3 to determine the classification loss for each label.

Yolo, a network that is entirely composed of convolutional layers (FCN) YOLOv3 uses the Darknet-53 feature extractor architecture, a more advanced feature extractor. Layers of convolution in YOLOv3 There are a total of 53 convolutional layers, with a batch normalization layer and a Leaking layer of ReLU activation. Applying a convolution layer and various filters to the images results in the creation of many feature maps. The map features are downscaled without pooling using a stride-based convolutional layer of 2. It helps avoid minor property losses that are frequently attributed to pooling in Fig.3.

Procedures for YOLO v3 object detection: ● The inputs are several photographs of shapes (m, 416, 416, 3).

- YOLO v3 sends this image to a convolutional neural network (CNN).
- The final two dimensions of the output seen above are flattened to yield a volume of (19, 19, 425):
- In this case, a grid of 19 19 cells produces 425 outcomes.
- Each grid has five anchor boxes, so 425 is equal to 5 * 85.
- 85 is equal to 5 Plus 80, where 80 represents the number of classes we're looking for and 5 stands for (pc, bx, by, bh, and bw).
- A list of bounding boxes is the outcome together with any classes that were found. Six integers serve as symbols for each enclosing box (pc, bx, by, bh, bw, c).
- If c is stretched into an 80-dimensional vector, each bounding box is represented by 85 values.
- To stop picking boxes that overlap, we then employ the Non-Max Suppression and IoU (Intersection over Union).

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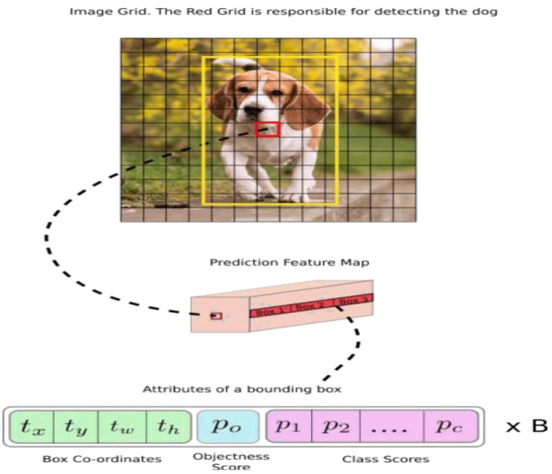

Fig. 3. Grid view of detected animal

3 Results and discussions

We have a model created using the esp32 camera in the specified manner from live stream footage. The suggested system is capable of identifying live objects and animals using the Yolov3 packages. The shortcomings of the current paradigm are addressed by the proposed model in Fig.4, Fig.5, Fig.6.

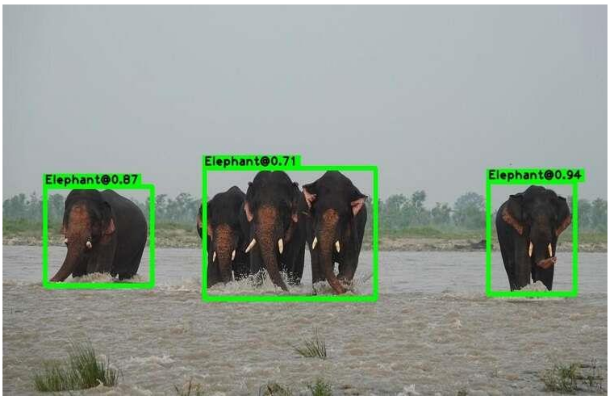

Fig. 4. Detected animal live transition eg: Elephant

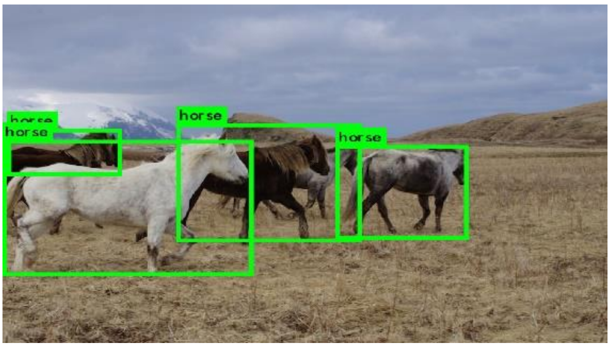

Fig. 5. Detected animal live transition eg: Horse

Fig .6. Detected animal live transition eg: Cow

4 Future work

This device not only offers protection but also uses RFIDs to tell an authorized individual from a burglar. To differentiate between animals and humans, we employ cascade classifiers based on the Haar feature. Furthermore, the system has proven to be reliable, stable, and suited for employing different experimental settings for balanced and imbalance when managing outdoor photography. We are developing numerous methods to improve the system's performance, including enlarging the dataset, applying more advanced CNN models, and taking advantage of the special characteristics of camera trap photos. We would investigate transfer learning in the direction of a fully automated wild animal recognition system to handle the issue of highly uneven data. We will shortly focus on developing a "hybrid" classification framework for wild animals, which will include an automated module that will act as a recommendation system for the ongoing Wildlife Spotter project, which is based on citizen research.

5 Conclusion

IoT and machine learning technologies can be used to safeguard crops from animal invasion, which is essential for the optimal growth of crops. Only a few of the strategies described in this study include the Raspberry Pi Processor, WiFi module, and real-time picture algorithm, which outperforms other algorithms in terms of performance, accuracy, and efficiency. In the future, an app-based paradigm might be created to enhance mobility and use. The aesthetics assessment (AA) and attention box prediction (ABP) networks, both of which share several initial convolution layers, are the two sub-networks that make up the suggested deep model. Using the determining-adjusting design concept, we created our model. The first cropping is determined by the ABP network as a bounding box encompassing the visually relevant area (attention-aware choice), and the best cropping with the highest aesthetic quality is then chosen from among various cropping alternatives created around the initial cropping. Several publicly accessible benchmarks have been put through a lot of testing, and in-depth analyses have been published on a variety of topics, such as the efficiency of each important component and the cost of computation. Our tests and thoughtful user research consistently show how successful and resilient our strategy is compared to current industry standards.

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