Animal Detection Based Smart Farming in Animal Repellent Using AI and Deep Learning

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Abstract- *Agriterrorism with regard to animal damage greatly affects the crop yield for farmers, resulting to some of them recording large losses. Farm animals like buffaloes, cows, goats and birds trespass in the fields trample the crops and this can only be destructive for farmers since they cannot constantly protect their shambas. Measures such as the use of barriers, wire fences, or personnel vigilance yield most of the time insufficient results. In addition to scarecrows, which enemies can easily bypass with many animals, farmers also employ human effigies.To control these problems, we introduce an AI-based Scarecrow system using video processing in real- time for crop protection from wildlife. The system uses a camera to record videos and analyzes them with YOLOv3, an object detection model together with OpenCV and the COCO names database. If any animal or bird is identified, then the system produces a sound alerting the animal not to invade the compound. Moreover, if an animal has been sensed for more than one minute consecutively, the system will alert the farmer sending him/her an e-mail and dialing the farmer`s phone number. This approach thus provides an efficient and automated way of protecting crops than depending on deterrent measures..*

Keywords- Crop Protection, Animal Detection, AI-based Scarecrow, Object Detection, Agricultural Monitoring, Sound Alerts, Automated Notifications, WildlifeDeterrent

I. INTRODUCTION

Livestock continues to pose a threat to crops through invasion and trespass, resulting in crop loss and huge loses. In the interest of adequately protecting crops, the farming industry needs productiveness solutions that are, effective, dependable, and preemptive. The objective of this project is to look at the potential and opportunities of applying the Disruptive Technology of Deep Learning to meet these challenges.

The traditional method of crop protection involves periodic inspection and/or the use of barriers that are either manually operated or mechanically activated, they have been found to be quite ineffective, inaccurate and cannot be easily or effectively scaled up for large fields. These methods involve a lot of labor and in addition do not offer real-time automatic reactions to threats meaning crops are at risk of damage and the farmer’s effectiveness in maximizing yields and protection is severely diminished.

To overcome these obstacles, the project employs surveillance systems based on Deep Learning, that employ both computer vision and machine learning in order to detect threats on the fly. The system can detect animals or intruders in the field using a YOLO (You Only Look Once) object detection algorithms. This guarantees fast, efficient and autonomous responses,significantly minimizing the time and energy that is taken while monitoring.

This paper highlights many benefits that can be derived from the Deep Learning-based system over the conventional means of protecting crops: First, the fact that the system can run an intrusion detection and intrusion classification in real time guarantee minimal crop loss from intrusions. Second, computer vision algorithms allow for a high level of accuracy in the identification of multiple types of threats to act on, so actions are only taken when required. Third, the system supports smart alerting tools such as sound playback, email, and phone alert, which will in one way assist the farmers to be in a position to attend to exigent circumstances promptly whether there is necessity of moving to the field or not. Last but not least the incorporation of camera monitoring makes it possible to get visual proof which may be used in order to explain to farmers in order to increase confidence.

The system also helps in identifying potential threats more accurately using machine learning, means that as often as new threats or more detailed scenarios appear, the system begins to recognize them more accurately. Real-time video processing melded with the capability of sending instantaneous email and phone alerts is a perfect solution for crop guarding against possible perils.

This project work seeks to redesign the way crops are protected by incorporating a more improve, autonomous and efficient Deep Learning technology. Its effective and efficient features such as the real-time monitoring of the crops, provision of smart alerts, and prompt means of cultivating and detecting the problem area would not only gain less manual labor but also less threat on the crops leading to high and secure productivity of farmers.

II. LITERATURE SURVEY

Adami, D., Ojo, M. O., & Giordano, S. (2021) Development of an Embedded Edge-AI-based Animal Repelling System for Crop Protection: Design and Evaluation. As part of this novel work, this paper proposes a smart agriculture system with emphasis on animal trespass protection, particularly Uganda's ungulates such as wild boar and deer through the edge computing. It uses YOLOv3 and the faster Tiny YOLO for real-time object identification on systems such as the Raspberry Pi and NVIDIA Jetson Nano. The system uses species-specific ultrasound signals to scare the animals and use IoT for linkages and control. The work evaluates the performance of models, power consumption, and the cost-to-performance ratio for the concept of edge-AI to help farmers in decision-making.

J Redmon, J & Farhadi, A, (2018). YOLOv3: An Incremental Improvement. As a continuation of the previous YOLO model development this paper covers the third version of the model which is widely used in real-time object detection. As a part of the series, there is YOLOv3 that splits the image into grids and then determines the coordinates of the boxes that probably contain an object and also the class probabilities of an object. It is good for real time applications since it will provide fast results without compromising accuracy, for instance in agriculture, the discrimination algorithm will easily detect intruders on the farmland and prompt defensive actions.

Viola, P. & Jones, M, (2001). A boosted cascade of simple features for real-time object detection. This brief study initiates the use of the Haar Cascade classifier, employed in face detection. In the approach, positive and negative images are employed to build a set of classifiers for on-line objects detection similar to farmer's face recognition or identification of strangers in your system. It can be connected with certain alarms to inform when an intruder is sensed around secured areas of agriculture.

Reddy KV, Goutham V Knowledge and practice: An Indian perspective Analysis of the year 2024. Edge AI in Sustainable Farming: An IoT Framework Based on Deep Learning to Protect Crops from Wildlife Predation. This paper proposes a real-time animal intrusion detection system based on TinyML with a lightweight deep learning model, namely EvoNet. It incorporates Internet of Thing for surveillance and prevention, with add-on that allow farmer to have a bird-eye view of threats from a remote control intelligent rover. The system integrates high energy efficiency, and high detection accuracy, it is a stable solution for protection of crops.

Korche, M., Tokse, S., Shirbhate, S., &Jolhe, S. P. (2021). Smart Crop Protection System. This study proposes a microcontroller-based crop protection system utilizing sensors and GSM modules for alerting farmers of nearby animal intrusions. Traditional approaches such as scarecrows and electric fences are complemented by modern technologies like motion sensors and wireless communication, offering real-time alerts and automated responses to protect farmlands from animals.

III. METHODOLOGY

The idea that can be implemented by applying Deep Learning in the context of the proposed system is the real-time protection of the crops by detecting animals and intruders. The above system aims at having the ability to automatically recognize threats and inform the farmer using sounds playback, emails, and phone calls. Real time video processing is based on the YOLO (You Only Look Once) algorithm for object detection at the heart of the system.

The system is divided into two primary components: Object Recognition and Detection and Alert System.

In this Object Detection component, the system employs the use of a camera to scan the crop field. The camera records live video streams, which then are analyzed with the help of the YOLOv3 algorithm. YOLOv3 breaks up the video frame into cells and computes a likelihood of danger or threat, such as recognition of animals or unfamiliar people by computing bounding boxes and class probabilities. This makes it possible for the system to identify multiple objects and do so in real time. When the system recognizes certain person for example the farmer no action is taken. However, whenever an unfamiliar person or an animal is sensed, the systems for alerting begin the process.

The Alert Mechanism consists of three steps:

1. Sound Playback: It triggers an animal based alert sound enough to scare out an intruder or animal once it has been noticed. Playsound library is used to play the sound file.

2. SMS Alert :When an unauthorized individual or animal is detected, the system initiates a real-time alert process. An SMS notification is immediately sent to the owner's mobile device, ensuring they are promptly informed about the

potential threat. The SMS contains essential details, allowing the owner to take quick and appropriate action to protect the area.

Each detection event includes date and time of occurrence, type of threat detected – animal or person – and action that the system has taken. This quickly makes way for future analytical works of trends and patterns concerning intrusions relevant in the protection of farmers' crops. Therefore, the Smart Crop Protection System established the use of Deep Learning-based object detection, real-time alerts, and automated notification for a reliable protection of crops. Efforts made in the design of the project include the use of YOLOv3 for detection of the intruders and a multimedia alert system so as to ensure farmers are provided with an efficient tool to prevent crop damage from people or animals.

The Smart Crop Protection System shall ensure protection to crops from intruders and animals; it is to include Deep Learning for surveillance and notification. The architecture entails both the object detection and the means for passing of the alert, which combines the security systems. The system by design constantly watches the crop field and gives alarms any time it detects a stranger or an animal. User Modules have features including; the capability to identify animals or intruders. When a potential threat is identified, the system plays sound to elude the intruder, also at the same time an image of the intruder together with a notification email is sent the farmer. In addition, if required, the system can even make a phone call to the farmer notifying him of an ongoing intrusion.

STEP-1: Camera feed in real time: By capturing live feed in the field, the system employs the use of a camera that provides video feedback.
STEP-2: Superior video analysis with YOLOv3: The frames captured by the video cameras are analyzed with the use of YOLOv3 that is capable of identifying the presence of any animals or any unfamiliar persons getting into the field.
STEP-3: Intruder detected: This is where the system identifies, through its cameras, an intruder; an animal or a person.
STEP-4: Sound alert activated: The system plays a animal based sound using playsound library to caution the intruder instanly.
STEP-5: On detecting an object, the system sends an alert SMS to the farmer. The SMS is delivered through an SMS gateway service.
STEP-7: The detection event is logged into the system and contains information regarding the object that has been detected as well as the time of detection and what occurred in response to the event.
STEP-8: Admins can get a list to look at the detection history of all instances: The admin has access to a list they can use to view all the images that the software detected, along with some timestamp and action.

Coco. Names Dataset:

The COCO dataset which expanded like "Common Objects In Context" has become one of the prominent datasets. well-known repository of difficult and good quality data aimed at computer vision tasks. Extensively, it gets acknowledged due to covering a vast array of and copious material. 22 embodies a sizeable repository for training and assessment of current-generation neural networks. The name "COCO" is not not only to do with the data set but also used to describe the format of the dataset. Concerning the current state of how datasets are organized and presented. COCO has turned into a reference for the to the task of building and evaluating computer vision models and algorithm, that has a great impact to other developments in object recognition, image segmentation and other fields of study.

Deep Learning Integration:

Deep Learning in Object Detection: It elaborates higher level abstractions of the data structures by using neural networks that contain many layers; and it is a subcategory of machine learning. In your project for object detection the use of CNN based method is utilized since it is more appropriate for such tasks as animals and intruders detection. Convolutional Neural Networks (CNNs): CNNs are the fundamental of the object detection algorithms like the YOLO. They function through a capability that embodies the spatial hierarchy of features inherent in input images such as edges,
textures and objects. Convolution Operation: The convolution operation applies a filter or kernel to indentify features from the input image. Every filter you slide across the image performs dot product analysis of filter with input at each position and gives you feature map.

Formula for convolution:

$$(I*K)(i,j)=\sum_{m}\sum_{n} I(i+m,j+n)\cdot K(m,n)$$

where:

I is the input image.

K is the convolution kernel (filter).

i,j are pixel positions in the output feature map. M,n are pixel positions in the kernel.

Activation Function (ReLU): After the convolution, an activation function (typically ReLU) is applied to introduce non-linearity into the model, allowing it to learn more complex patterns. Formula for ReLU:
ReLU(x)=max(0,x)
This function sets all negative values in the feature map to zero, keeping positive values unchanged.

Pooling (Downsampling): Pooling layers reduce the spatial dimensions of the feature maps, making the network computationally efficient. Max pooling is a common technique where the maximum value in a patch of the feature map is selected.
Formula for max pooling:
P(i,j)=max(F(i+m,j+n))
m,n
where:
F is the feature map.
i,j are the pixel positions.
m,n define the pooling window.

Fully Connected Layer: After several layers of convolution and pooling, the feature maps are flattened into a vector, which is then passed through fully connected layers for classification or detection.

YOLO uses a single CNN to predict bounding boxes and class probabilities directly from the input image. The image is divided into grids, and for each grid cell, YOLO predicts a bounding box if an object center falls within that grid cell.

Localization loss (for bounding box position and size):

$$\text{Localization Loss} = \lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{obj} [(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 + (w_i - \hat{w}_i)^2 + (h_i - \hat{h}_i)^2]$$

Confidence loss (for object presence):

$$\text{Confidence Loss} = \lambda_{noobj} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{noobj} (C_i - \hat{C}_i)^2$$

Classification loss (for class prediction):

$$\text{Classification Loss} = \sum_{i=0}^{S^2} 1_i^{obj} \sum_{c \in classes} (p_i(c) - \hat{p}_i(c))^2$$

Real-time Detection: For the object detection the system employs YOLOv3 algorithm, which is very effective for identifying animals and intruders in the field. Each detection is rendered online and in real time for timely reaction to the problem.
Multimedia Alerts: The system utilizes the ability to play a sound, send an alert SMS, its guarantees that the farmer is informed of intrusion.
Transparency and Accountability: Every detection event is recorded and the farmers are able to study previous intrusions to better Le the manage the security threats.

IV. PROPOSED ALGORITHM

YOLOv3 as an acronym for You Only Look Once, version three is a real-time object detection framework that is purely based on convolutional neural network. It partitions the input image into a grid and forecasts the parameters of the objects' shape and the probability of the image belonging to a particular class. From previous versions, YOLOv3 brings several enhancements concerning the correct rate and detection of smaller objects and in more complex environments. As one of the unique features of YOLOv3, the model can detect a wide range of objects. simultaneously. This is attained by an object detection procedure that divides the input image into a grid, and each cell predicts positions of 4 boundaries and the probability of an object exist inichten within its boundaries. These predictions are then fine-tuned when using the anchor boxes which in turn boost detection accuracy. Such a feature of multiple classes is vital in situations that require Like it in a case of shape recognition for traffic surveillance or robotics where several objects are recognized in a single frame. The next characteristic worth discussing is that YOLOv3 is a very fast model - this means that it is suitable for real-time projects.

Proposed algorithm architecture

It uses feature extractor; Darknet-53, which is a depth architecture of 53 convolution layers. The architecture is divided into several stages: Feature Extraction with Darknet-53: In Darknet- 53, convolutional layers followed by batch normalization and Leaky ReLU layers are applied one after the other to construct depth in creating a powerful representative of the image. These layers enable a capture of spatial hierarchies of objects from learning low level features of objects such as edges and textures and high level features such as the shapes of the objects Convolution Layer Formula:

$$Z = (I * K) + b$$

Where I is the input, K is the kernel, and b is the bias term.

Residual Blocks: YOLOv3 uses residual connections inspired by ResNet, which allows gradients to flow through deeper layers and mitigates the vanishing gradient problem. Residual blocks can be defined as:

$$x_{l+1} = f(x_l) + x_l$$

Where f(xl)f(x_l)f(xl) is the output of convolution layers and xlx_lxl is the input to the layer.

Multi-scale Detection: YOLOv3 performs detection at three different scales to improve the detection of small objects. It predicts bounding boxes at three different feature map sizes, capturing objects of varying sizes by detecting on:

A 13x13 feature map (for large objects).
A 26x26 feature map (for medium objects). A 52x52 feature map (for small objects).

Anchor Boxes: Each grid cell predicts multiple bounding boxes with pre-defined shapes known as anchor boxes. YOLOv3 refines these anchor boxes during training to better match the actual objects.

Anchor Box Loss:

$$L_{box} = \lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{obj} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 + (w_i - \hat{w}_i)^2 + (h_i - \hat{h}_i)^2 \right]$$

Class Prediction: YOLOv3 predicts class probabilities using logistic regression. Each box predicts the probability of containing a particular object class, and this is done using binary cross-entropy loss rather than softmax, allowing for multiple labels per box.

Class Loss: The Smart Crop Protection System uses YOLOv3 algorithm to identify animals and intruders in real time mode. Here's how YOLOv3's architecture supports your system's objectives: Multi-object Detection: With regards to feature that gives YOLOv3 advantage over other object detection models is that it scans for several objects in a single go, which is very important when it comes to looking for different animals and intruders on the field. This makes the monitoring very efficient and able to alert security of an intrusion very promptly.

Anchor Boxes and Real-time Capability: The anchor boxes and the multi-scale detection feature in the model make the system capable of detecting animals of different sizes which are crucial for product differentiation of a small and a large potential threat. This form of processing is important for real time alerts like playback of any sound to ward off animals or send an e-mail to the farmer.

High Accuracy for Critical Tasks: YOLOv3's architecture makes it easy to detect the exact location and identity of the farmer or any other familiar object as compared to detecting a completely new threat. This effectively means that instead of being flooded by several alerts, the system gets to highlight what is important to the farmers by eliminating actual fakers.

The proposed system incorporating YOLOv3 provides the ability to coordinate and perform real-time surveillance functions, alert handling and detection of multiple objects accurately within a dense environment – all of which would be valuable for agricultural protection.

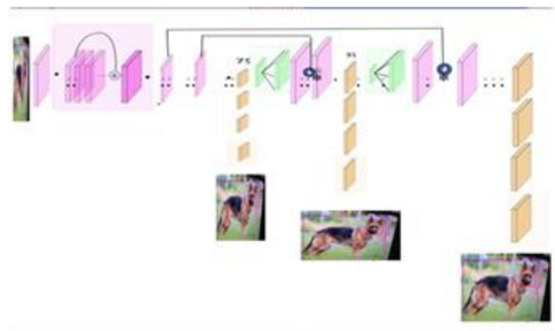

Fig 2

How proposed algorithm Works

Real-Time Video Feed: The system is constantly recording real time video feed of a camera tracking the crop field.

Frame Processing: That is why, the captured frames are introduced to the YOLOv3 algorithm for the subsequent analysis. Compared with Fast R-CNN that takes multiple passes over the image, YOLO achieves object detection in real time.

Grid Division: YOLO divides the image into an S×S grid, To achieve this YOLO splits the picture into 823530 S×S rectangles. In each cell of the grid, regression of bounding boxes and classification of class probabilities for objects with center in that cell are done.

Bounding Box Prediction: In particular, for each grid cell YOLO assigns a fixed number of bounding boxes.

Each bounding box includes:

Coordinates: Center coordinates (x,y) and width (w) and height (h).

Confidence Score: Shows the probability that the box contains an object, how accurate a box the model is.

Class Probability Prediction: Each grid cell they also compute the class probabilities of new objects as well. These probabilities tell us the probability of the given classes, for example, animal, person and so on.

-Maximum Suppression: After estimating bounding boxes and class probabilities, YOLO finally has suppressed the overlapping, redundant boxes using the non-maximum suppression method. This retains only the box of higher confidence for each object that has been detected from a scene. Object Detection: The resulting frames contain rectangular outlines drawn around animals or intruders detected (depending on the network used) marked with their class and respective confidence levels.

Real-Time Alerts: When the system detects an unknown person or animal with a confidence score above a predefined threshold, it triggers the alert mechanisms: Sound Playback: To scare away the intruder. SMS Notification: The farmer is notified through SMScontaining a picture of the captured object.

Logging and Monitoring: Every triggering event is documented and includes the object type detected, time when the detection was made and the actions that followed. This leads to capability to watch and analyze intrusions over a time space.

Advantages Associated with Employing YOLO on our Project

1.Speed: Due to the latter usage of the architectural components of YOLO, the identified threats can be processed in real-time.
2.Accuracy: It reduces false positives by making sure that alerts distance itself from false negative detections whilst YOLO has high accuracy that makes it identify multiple objects accurately.
3.Scalability: This means that the system can be loaded on edge devices and used in the different contexts of agriculture.

SMS Alert System:

This streamlined SMS alert system ensures that farmers receive timely warnings about potential threats, enabling them to take quick action and minimize damage to their crops.

Confusion Matrix:

you are implementing object detection, the confusion matrix can be implemented to assess the performance of for example YOLOv3. The matrix shows the accuracy of the identified objects from the detected ones, whether they are animals, intruders or the farmer was to be expected. Once more the matrix will contain the actual labels of the objects and the labels predicted by the detection system.

Breakdown of Terms:

True Positive (TP): The system correctly detects an animal or intruder (correct classification). True Negative (TN): The system correctly recognizes the farmer or correctly identifies that no detection should be made.

False Positive (FP): The system mistakenly detects an animal or intruder when it is actually the farmer, or there was no detection.

False Negative (FN): The system fails to detect the presence of an animal or intruder, or mistakenly classifies the farmer as a threat.

Example Scenario:

Let's say your system runs 100 tests with the following results:
60 animals were correctly identified as animals (TP).
5 animals were wrongly classified as intruders (FN). 10 intruders were correctly identified as intruders (TP).
8 farmers were wrongly identified as animals or intruders (FP).
15 instances had no detection, and the system correctly did not raise an alert (TN).The matrix might look like this:

Class Name	Precision	1-Precision	Recall	1-Recall	f1-score
Class0	0.9231	0.0769	0.9231	0.0769	0.9231
Class1	1.0000	0.0000	0.4545	0.5455	0.6250
Class2	0.6800	0.3200	0.9444	0.0556	0.7907
Class3	0.7500	0.2500	1.0000	0.0000	0.8571
Accuracy	0.8500				
Misclassification Rate	0.1500				
Macro-F1	0.7990				
Weighted-F1	0.8403				

Statistical measures:

Training Set					
TARG / TPUT	Class0	Class1	Class2	Class3	SUM
Class0	60 50.00%	5 4.17%	0 0.00%	0 0.00%	65 92.31% 7.69%
Class1	0 0.00%	10 8.33%	0 0.00%	0 0.00%	10 100.00% 0.00%
Class2	3 2.50%	5 4.17%	17 14.17%	0 0.00%	25 68.00% 32.00%
Class3	2 1.67%	2 1.67%	1 0.83%	15 12.50%	20 75.00% 25.00%
SUM	65 92.31% 7.69%	22 45.45% 54.55%	18 94.44% 5.56%	15 100.00% 0.00%	102 / 120 85.00% 15.00%

V .EXPERIMENTAL RESULTS

A. Identifying Animal and Making Sound Image

In addition to detecting unknown individuals, the system is equipped with functionalities to identify animals that may pose a threat to the crops. Utilizing advanced image processing techniques, the system analyzes incoming footage to detect animals such as deer or livestock. Once an animal is identified, the system triggers a sound alert to deter the animal from entering the crop area. This proactive approach minimizes damage and enhances crop protection.

SMS Alert Getting Image

When an unauthorized individual or animal is detected, the system initiates a real-time alert process. An SMS notification is immediately sent to the owner's mobile device, ensuring they are promptly informed about the potential threat. The SMS contains essential details, allowing the owner to take quick and appropriate action to protect the area.

VI. CONCLUSION

It was pointed out that the Smart Crop Protection System was able to implement the use of artificial intelligence to improve agricultural safeguarding. Using enhanced identification technologies, the system can guarantee that alerts are provided only when an unfamiliar human and/or animal is detected. The objectives of the project were achieved by developing a method of tracking crop areas and hence reducing risks such as theft and damage.

Using real-time image processing, sound alarms, and notifications, the system presents a perfect solution for the crops protection. This new concept does not only amplify security but also brings Or Good to owners as they are assured of the security of their investments in the agricultural field. Thus, with further development in agricultural technology, the Smart Crop Protection System proves the importance of adopting the application of AI in farming activities achieving smarter and more secure farming.

VII. FUTURE SCOPE

The Smart Crop Protection System Using AI offers immense potential for further innovation and scalability. As AI and machine learning technologies continue to advance, future improvements in the system can make it easier to use, help more farmers get access to affordable crop protection tools, and open up new policy options for safeguarding crops.

1. Enhanced AI Models: With the continuous evolution of AI, the system can incorporate more accurate object detection and image classification models. This could lead to more precise identification of animals and people, reducing false alarms and enhancing system reliability.
2. Integration with IoT: By integrating with the Internet of Things (IoT), the system can interact with sensors, cameras, and automated devices in real-time. For example, if an animal is detected, IoT devices could automatically trigger fencing mechanisms or initiate protective measures in the field, offering a fully automated crop protection solution.
3. Cloud-Based Monitoring: A cloud-based architecture could allow farmers to access live feeds, notifications, and reports from remote locations. This would also enable AI model updates to be pushed remotely, ensuring that the system stays up-to-date with the latest improvements.
4. Data-Driven Farming Insights: The system could collect and analyze data over time to provide insights into animal movement patterns, weather conditions, and potential threats. These data-driven insights could help farmers make better decisions regarding crop protection and farming practices.
5. Integration with Government Policies: In the future, systems like this could be integrated with government initiatives to protect crops on a larger scale. Governments could incentivize the adoption of such AI-based systems by offering subsidies or linking them with insurance programs, ultimately enhancing food security.

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