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CNN Based Animal Repelling Device for Crop Protection

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Abstract. The use of modern IoT technology in agricultural regions has been the subject of much research and several attempts. This paper's main goal is to protect the crop against animal assaults. Traditional methods apply the same level of security to all sorts of animals identified using a Passive IR sensor, and only single-stage protection is used. With the aid of Support Vector Machine and Convolution Neural Network algorithms, the photos were properly recorded and recognized, and the information was delivered to the farm owner via IoT devices. A section of the farm was used to create the project. On either side of the entry, cameras were installed to record images for processing to identify the animals, and different levels of security were applied based on the animal identification. The dB level of the reciprocating sound will fluctuate according to the animal. Different levels of protection and different forms of protection are used depending on the classification of the animals. Making noise and lighting from the opposite side sends the animal out of the farm in the first degree of protection. The collected photographs are sent to the owner at the second level. The suggested method's accuracy may be determined by comparing it to the standard technique's complexity, implementation cost, reciprocating time, and animal detection accuracy.

Keywords: Animal Classification, CNN, IoT, Crop Protection, Deep Learning.

1. Introduction

Agriculture is critical to many countries' economies across the world. Agriculture remains the economy's backbone, despite economic advances. It contributes to the GDP of the country [1]. Agriculture provides food for humans while also providing a range of raw materials for industry. Animal interference and fires in agricultural areas, on the other hand, will result in severe crop loss. The crop will be damaged altogether. A considerable proportion of farmers will lose their livelihoods [2].
To avoid financial losses, it is necessary to protect agricultural fields and farms against animal and fire damage. In our planned study [3], develop a technique to prohibit animals from entering the farm to solve this issue. The main purpose of this project is to install an intruder alarm system on the farm to minimize animal and fire losses. The crop is protected from harm by these intruder alarms, which increases agricultural productivity. Animals and people will not be harmed by the embedded development system. The project's purpose is to develop a smart security system for agricultural safety [4-7].
When compared to other wildlife monitoring methods, camera traps are the most successful and cost-effective option for a variety of species [8]. Hundreds of sensors are presently rotating over thousands of sites [9], sometimes with citizen scientists' help [10].

Ambitious programs are growing the scale at which cameras are used on the terrain. Convolution Neural Network (CNN) approaches have recently been shown to be extremely effective in categorizing images and recognizing objects [11]. CNN is a popular deep learning model. Convolution, pooling, and classification make up CNN's basic structure. Convolution layers are translationally and locally invariant operators between the input picture and filters [12]. Downsampling is used in pooling layers, which might be maximal or average. CNN uses stochastic gradient descent to learn pixel-to-classifier feature hierarchy [13]. Categorization layer will assign this work three grades. Grades reflect human, animal, and environmental categories. If computer vision can identify the moving object in an image and remove the background, it might be used to evaluate camera trap photos [14]. Moving trees, shifting shadows, and sunspots make outdoor camera trap photos tricky. Foreground detection or in-camera traps can find organisms in the background. Pixel-by-pixel or region-based techniques can determine foreground pixels [16]. Pixel-by-pixel analysis is most common. The pixel-level background model is provided by nonparametric background samples [17], resilient principal component analysis (RPCA) [19], and the median pixel value [17]. False positives and the inability to distinguish animal and human products have impeded these efforts [20].

2. Test system description

In the literature, numerous strategies were explored, and these methods were compared in terms of processing time, detection accuracy, and reciprocating time. The approaches listed below were discussed and contrasted. The detailed block diagram of the test system is shown in Figure 1. It is made up of the monitored agricultural land's sample area. The animal replication system consists of a solar panel with a battery to operate remotely without the need for external power, a camera mounted beneath the solar panel to capture images and video of the farm, and speaker and lighting equipment mounted at the bottom of the pole to produce necessary replication based on the detecting animal. The repelling device has the capability to produce different sounds with different levels of sound depending on the animal.

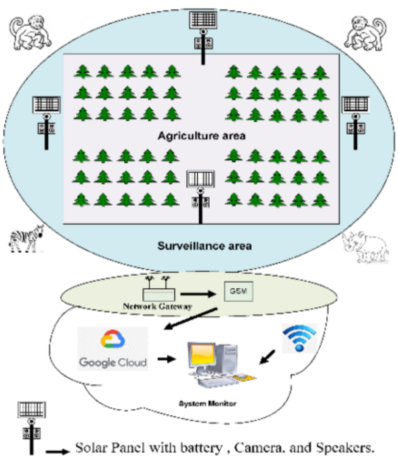

Figure 1. Block diagram of the proposed model

3. Methodology

To complete the assignment, many techniques were investigated. On the identical test settings, four prominent approaches were evaluated and the outcomes were compared, total ten animal were considered list in table 1. Below is a full algorithm that explains the processes.

3.1. Convolutional neural networks (CNNs)

In recent years, as computing power has increased, CNN has emerged as the dominant algorithm in computer vision. Within the context of this project, Exception is one of the top-performing architectures that has been transferred for further improvement. Similar to Inception-v4, GoogLeNet, and ResNet, but with a depth-separable convolutional layer in place of inception modules. After applying a single spatial filter to each feature map in the input, the system then looks for cross-channel correlations.
The image after being processed by a convolutional neural network is shown in Figure 2.

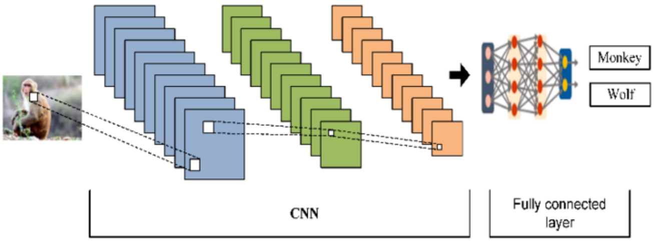

Figure 2 Image processing using CNN

It needs fewer parameters, memory, and calculations than traditional convolutional layers, in addition to providing greater performance. The CNN algorithm is depicted in Figure is a flowchart that represents the image processing using CNN, or convolutional neural networks, are multilayer neural networks that are used to analyze images and detect objects. In 1988, Yann LeCun established the first CNN, which he dubbed LeNet. It recognized characters such as ZIP codes and digits. CNN is commonly used to locate abnormalities, analyze medical imaging, forecast time series, and uncover anomalies.

3.2. Recurrent Neural Networks (RNNs)

Recurrent Neural Networks are divided into four categories: Figure 3 depicts a) One to One, b) One to Many, c) Many to One, and d) Many to Many. Long Short-Term Memory units can also be found in recurrent neural networks (LTSM).
The algorithm of RNN was shown in figure 3b. RNNs with directed cycles can be utilized to supply the current phase with LSTM outputs.

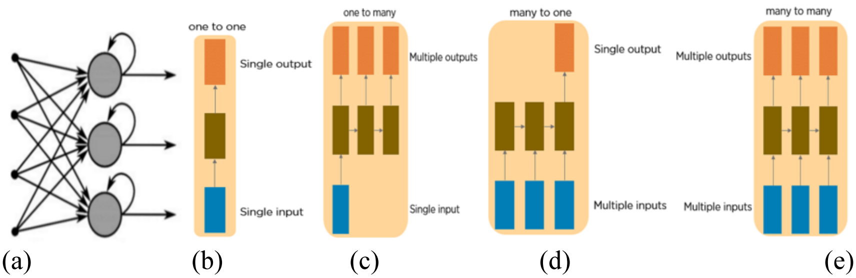

Figure 3 a) Recurrent Neural Network b) one to one c) one to many d) Many to one e) Many to many

3.3 *Multi-layer Perceptron (MLP)*

MLP differs from logistic regression in those one or more non-linear layers, known as hidden layers, can exist between the input and output layers. MLP's capacity to train non-linear models is one of its primary advantages. However, there are significant drawbacks, including a non-convex loss function and the need to tune for the number of hidden layers and neurons. MLPs are a great place to start if you're interested in learning more about deep learning. The detailed flow chart of the MLP represented in Figure 4.

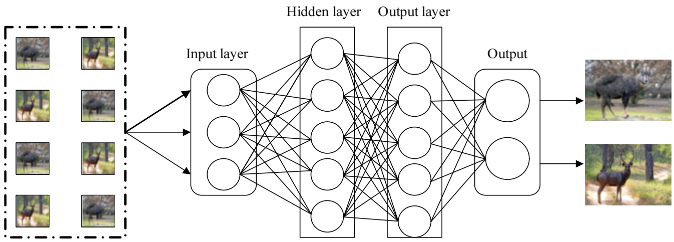

Figure 4. MLP classification

3.4 *Generative Adversarial Networks (GANs)*

The discriminator learns to tell the difference between the bogus data generated by the generator and the genuine sample data. The generator generates fraudulent data during early training, and the discriminator soon learns to recognize it as such. To update the model, the GAN delivers the results to the generator and discriminator.

4. Experimental processing

Using a 96-megapixel camera, ten images of wild animals were captured in various weather situations. To manage enormous images, image resolution must be increased, which increases memory and processing requirements. To increase image variety and enhance image representation, the data needed to be confirmed before training the image. Jitter, picture rotation, flipping, cropping, multi-scale transformation, hue, saturation, Gaussian noise, and intensity were used to preprocess the images. The accuracy and durability of identification were improved through data augmentation.

The system airflow passively cools the T4. For quicker ray tracing, the virtual machine features RTX hardware acceleration. The GPU of the T4 has 16 GB of GDDR6 RAM (GPU). Low latency and fast throughput for deep learning inference were goals for this GPU's architecture.

The greatest tool for displaying neural network training and evaluation metrics is Tensor board. In most cases, we'll need to examine specifics like the performance of a model's validation data. We must assess the validation data when the accuracy and loss of the training and validation data are insufficient. Visual aids are confusion matrices. A confusion matrix, also known as an error matrix, is a special table structure used in machine learning that illustrates the effectiveness of a method for statistical categorization (in unsupervised learning it is usually called a matching matrix). The columns represent real instances, while the rows represent expected examples for each class (or vice versa). The term "mixing" relates to how obvious it is when a system combines two different sorts of data. To comprehend the complexity, precision, and validity of deep learning algorithms, a confusion matrix was constructed for this study. The confusion matrices for the four approaches are compared in Table 1. The intricacy, identification time, and reciprocation time of each approach were compared. Other methods are inferior to the CNN approach. CNN performs better than methods that use adjustable input and output layers. The input and output layers of CNN are constant.

Table 1. A comparative analysis

S. No	Method	Complexity	Classification time in ms	Time is taken for Reciprocating Action ms	Classification Efficiency
1	CNN	Low	140	194	92.4
2	RNN	Low	156	210	91.2
3	GAN	Low	149	203	91.6
4	MLP	Medium	198	252	91.3

5. Conclusion

The test was carried out to categorize the numerous wild animals to safeguard the crops. Once the animals have been identified, reciprocal action must be taken as part of the protection program. The findings of the study, which used deep learning technologies, suggest that wild animal assaults on crops can be avoided. With an identification accuracy of 92.4 percent and a reciprocation time of fewer than 200 milliseconds, CNN outperformed the other approaches. All of the approaches were validated using the same software test system, which included python code and tensorflow.

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