AIRep: AI and IoT based Animal Recognition and Repelling System for Smart Farming

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Abstract
Agriculture is becoming more automated, with technologies such as Deep Neural Networks (DNN) and the Internet of Things (IoT) being used to build complex tracking, monitoring, and control infrastructures. The successful management of interactions with non-agricultural ecosystem components, such as wildlife, is an important open challenge in this constantly changing environment. Preventing agricultural damage from wild animals is one of the key worries of contemporary farmers. Traditional solutions vary from the lethal (e.g., shooting) to the non-lethal (e.g., trapping) (e.g., scarecrow, chemical repellents,organic substances, mesh, or electric fences). Current techniques, on the other hand, often pollute the environment, which is harmful to people and ungulates, as well as being prohibitively costly, needing substantial maintenance, and prone to failure. In this study, we integrate artificial intelligence computer vision with deep convolutional neural networks to develop a system that can detect and recognise many sorts of animals, then employ ultrasonic emission suited to each species to keep them away. Edge computing devices can detect animals and activate the camera, then use deep convolutional neural network (DCNN) software to identify the target and interact with the Animal Repelling Module to tell it what sort of ultrasonic to emit in response.

Keywords: Animal Recognition, Repellent, Artificial Intelligence, Edge Computing, Animal Detection, Deep Learning, DCNN.

1.INTRODUCTION

Agriculture has gone through many revolutions, including the domestication of animals and plants a few thousand years ago, systematic crop rotation and other advances in agricultural practise a few hundred years ago, and the "green revolution" of the last several decades, which included systematic breeding and widespread use of man-made fertilisers and pesticides [1]-[4].

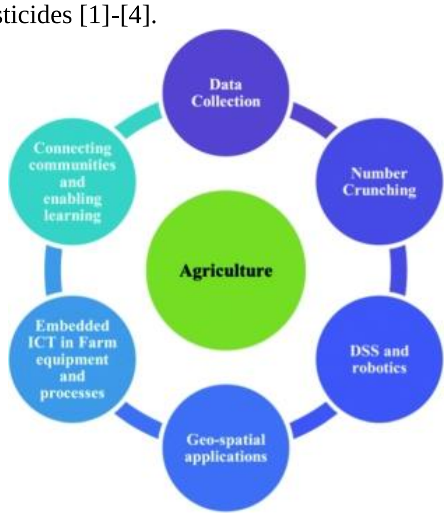


Figure 1.1. Agriculture and ICT innovation

2.RELATED WORKS

2.1.Smart Agriculture and Precision Farming Use Cases

Weeding using mechanical weeders

Weeds diminish agricultural output by obstructing light and nutrient intake, as well as providing bug shelter. As a consequence, farmers now have access to a tool that was previously unavailable: one that is not dependent on human labour.

We're going to attempt something new this year: mechanised harvesting.

Agricultural firms are losing money owing to inefficiency and delayed output due to a lack of automation. As a result, autonomous harvesting devices have been developed and are now commercially accessible. The computer can determine if something is a fruit or vegetable, and then utilise the camera to give the arms picking instructions.

• Plant diseases may be discovered and recognised.

They identify illnesses using AI algorithms and assist agricultural enterprises in locating and treating contaminated areas.

AI algorithms for disease detection might be built into greenhouse cameras, drones, and other agricultural machines.

Farmers can respond to their crops before disease outbreaks turn disastrous, thanks to better disease detection.

Watering systems that are targeted and zero-waste efforts

Smart agricultural applications that employ IoT to increase productivity and efficiency include animal tracking, vehicle tracking, field observation, and inventory monitoring. Sensor data analysis is used in precision farming to make informed choices.

Smart mapping and sensing

Internal and exterior sensors are used by connected agricultural equipment to monitor the climate in real time. With the aid of these sensors, you can reliably monitor humidity, precipitation, and temperature. Farmers may use environmental data to assist them pick crop types that are best suited to their region's weather patterns.

• Monitoring fruit output and crop health

Sensors that assess soil moisture might help with water saving measures.

To handle data and monitor the state of crops and soil, deep learning algorithms and computer vision are utilised.

Predictive analytics [6] - [10] use machine learning algorithms to analyse acquired data and predict the influence of environmental conditions on agricultural yield.

3. PROPOSED WORK

DCNN employs artificial intelligence to recognise animal species and then uses focused ultrasonic emission to scare them away (i.e., different for each species). The design, implementation, and evaluation of an intelligent smart agricultural repelling and monitoring IoT system based on integrated edge AI that can recognise and discriminate between a broad range of animals and give ultrasonic sounds customised for each species. It's feasible that this integrated technology will help farmers and agronomists make better decisions and manage their operations.

The feat of animal recognition was accomplished using deep learning in the form of Convolutional Neural Networks (CNNs).

• DCNN DCNN DCNN DCNN DCNN DCNN

In the identification and categorization of images, Convolutional Neural Networks (CNNs) have shown to be quite successful. CNNs are feed-forward neural networks with several layers.

CNNs are made up of filters, kernels, or neurons, which include weights, parameters, and biases that the programmer may change. Each filter is a convolutional modification of the input signal that may or may not contain non-linearity. A standard configuration for a convolutional neural network is shown in Figure 3.1. Convolutional, pooling, ReLU, and fully linked layers are among the numerous layers that make up CNN.

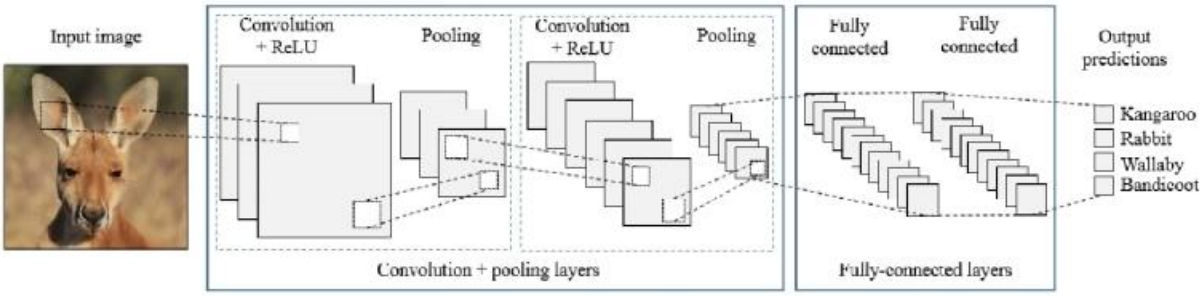


Figure 3.1.CNN

4. RESULTS AND DISCUSSION

This part creates a visual showing the accuracy and loss for each epoch during training and validation. The loss function is computed over all data items at each epoch, resulting in a quantifiable loss measure, however the curve shown after each iteration only represents the loss across a fraction of the whole dataset.

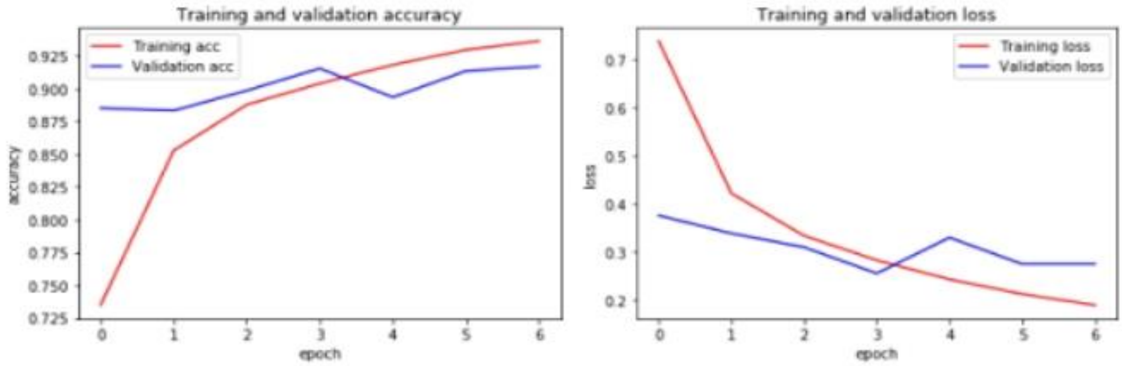


Figure 4.1. Training and Validation accuracy and loss graph

In studies, top-1 and top-5 accuracy on E2 were 80.6 percent and 94.16 percent, respectively, which is much better than the imbalanced dataset E1 (Fig. 7.2a). The accuracy of the combined CNN (Top-5) is shown against time in training and testing in Figure 7.2b.

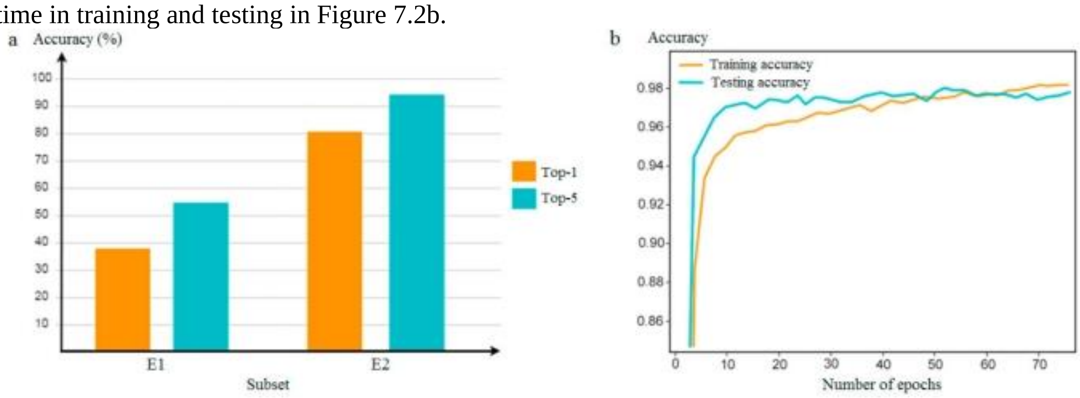


Fig.4.2. (a) accuracy of the joint CNN (Top-1 and Top-5) during training; (b) training and testing accuracy of the joint CNN (Top-5).

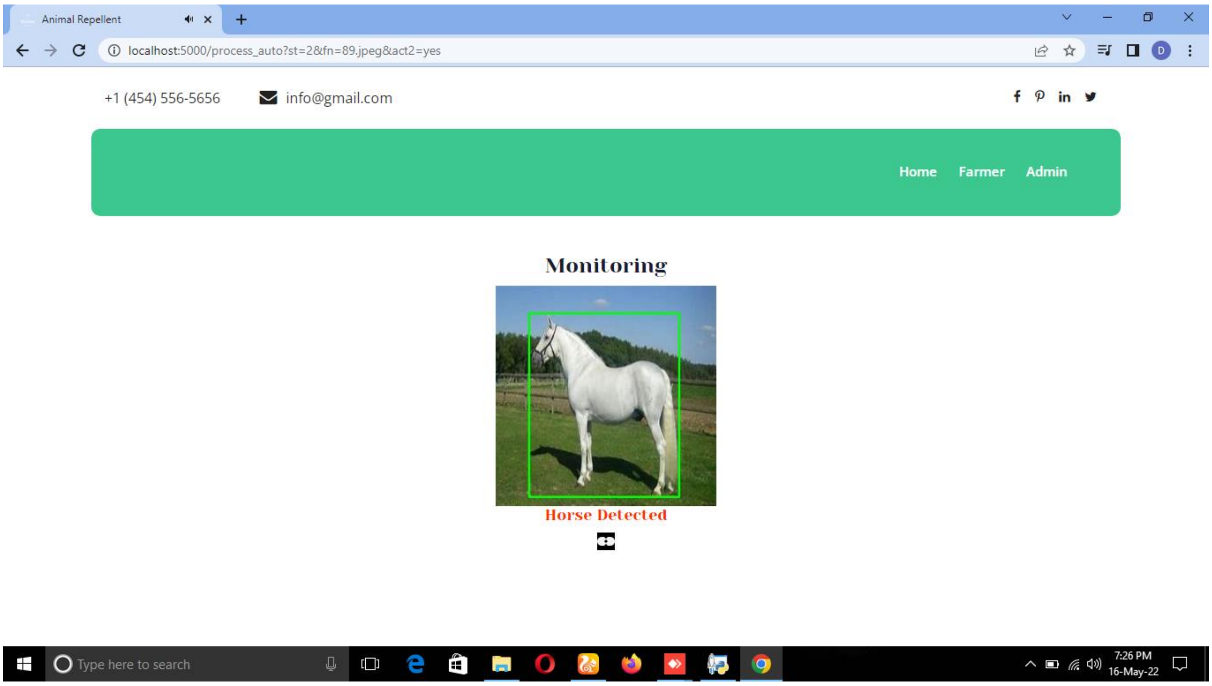
In the first attempt, a single-branch support vector machine was used instead of muzzle and contour information. The suggested combined CNN was executed in the second experiment according to the point-awarding criteria. Tables 1 and 2 demonstrate the average precision (AP), miss rate (MR), and false positives (FP) values for dataset E2 (FP).

Table 4.1.Animal recognition results using a single branch SVM.

Animals	**AP, %**	**MR,%**	**FP,%**	**Animals**	**AP, %**	**MR,%**	**FP,%**
Goat	78.83	12.2	11.3	Goat	76.52	8.4	16.3
Cow	80.64	9.4	14.8	Cow	81.3	7.8	12.5
Elephant	73.88	15.1	18.6	Elephant	75.54	14.2	17.9
Deer	76.74	13.7	17.4	Deer	69.88	19.6	22.4
Horse	80.91	8.9	16.1	Horse	63.85	24.2	26.9
Pig	79.72	8.1	18.2	Pig	79.21	16.3	18.7

Table 4.2.Animal recognition results using the joint CNN.

Animals	**AP, %**	**MR,%**	**FP,%**	**Animals**	**AP, %**	**MR,%**	**FP,%**
Goat	83.37	10.7	9.7	Goat	81.93	6.9	14.4
Cow	84.29	9.1	13.2	Cow	85.69	7.1	10.8
Elephant	79.13	12.4	16.3	Elephant	79.14	12.3	14.7
Deer	80.21	11.8	16.5	Deer	75.35	18.6	19.8
Horse	84.9	7.9	12.9	Horse	69.52	21.6	24.8
Pig	83.07	8	15.6	Pig	81.23	14.9	17.2



5. CONCLUSION

In the agriculture business, farm security is becoming more popular. An Animal Repellent System is created to employ sound and light to frighten the animals away, and a vision-based system is constructed using Python and OpenCV. If an animal is identified, the edge device uses its DCNN Animal Recognition model to identify which kind of ultrasound to emit and then sends that information to the AnimalRepelling Module. This study gave the first example of a real-time monitoring system driven by AI for analysing animal-caused crop damage. This kind of technology might help agronomists and farmers operate their businesses more efficiently.

6. FUTURE ENHANCEMENT

In addition, as previously mentioned, the suggested architecture may leverage numerous picture compression algorithms to minimise notice delivery time.

7.REFERENCES

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