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Animal Recognition using Deep Learning Architecture

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Abstract:

In this study, we've addressed the animal recognition problem by employing a deep learning architecture. The recognition problem is solved by using VGG16 model. The model is trained in Google Colab environment. The model is trained on the primary dataset. This dataset has 4 classes of Indian cow, each class has collection of images of one specific cow. The cow1 and cow2 class have 27 images each whereas cow3 class has 22 and calf class has 10 images. The loss value we got after 1000 step is 0.05. Out of 40 images of cows, the model successfully recognized 28 cows, giving it a 70 percent accuracy value of the model. This trained model holds potential applications in various sectors such as animal husbandry, zoos, and pet shops, where accurate animal classification is essential. We anticipate that this study will serve as a valuable resource for researchers, encouraging them to develop additional deep learning models to address animal classification challenges.

Keywords: CNN, VGG16, Deep Learning, Object detection, computer vision.

Introduction:

Throughout history, animals have held a significant role in the lives of humans. We have classified animals into three main categories: pets, farm animals, and wild animals. Pets are animals kept for companionship, entertainment, or protection, with cats and dogs being the most popular choices. Farm animals play a crucial role in agriculture and encompass species like cows, bulls, and buffaloes. Domesticated animals fall into the first two categories, while non-domesticated animals belong to the third category, residing in natural habitats. These include creatures like lions, tigers, and leopards. We can employ classification to group animals by their species, and recognition to accurately identify individual animals.

Farmers depend on their animals to meet their daily requirements, and they truly understand the value of these animals. This necessitates the need to differentiate between their own livestock and those owned by others. As the practice of animal husbandry has advanced, numerous techniques that have been in use for millennia have emerged. Typically, farmers establish the identity of an animal shortly after its birth, often within a matter of hours or days. Animal identification is an integral aspect of livestock management, although it is sometimes overlooked. There are various methods available for identifying animals, including the use of ear tags, ear tattoos, count tags, branding, and ear notching. Some of these identification methods are temporary and can potentially cause permanent harm to the animal. Therefore, automated identification proves highly advantageous in such situations, as it avoids any physical harm to the animal. Biometric identification presents one avenue for automatically identifying animals, albeit it necessitates the storage of the animal's unique identifying features in a database. These features may include iris prints, nose prints, retinal patterns, facial patterns, color patterns, and more.

However, there are several challenges that must be overcome to make biometric systems feasible in this context. First, there's the need to collect data from the animal to populate the database. Second, the animal must remain still during the recognition process; otherwise, the system won't be able to capture the animal's data accurately, leading to identification difficulties. In order to address these challenges, we propose an automated method for classifying and recognizing animals using deep learning techniques [1]. Our proposal entails recognizing animals by utilizing the provided database. For instance, this would involve the recognition of a specific cow within the category of cows.

The proposed methodology holds great potential for applications in animal husbandry, zoos, and various other sectors that demand animal monitoring [4]. However, our primary recommendation is to employ the presented model to tackle the challenge of animal identification within the animal husbandry industry. Farmers stand to gain numerous advantages from this approach, including:

- **Automatic Animal Counting:** The ability to count animals automatically, reducing manual effort and ensuring accuracy in tracking livestock numbers.
- **Automated Individual Animal Identification:** The capacity to identify individual animals automatically, facilitating efficient management and record-keeping.
- **Ownership Verification:** The capability to verify animal ownership, which is essential in preventing disputes and ensuring proper management of livestock.
- **Missing Animal Information:** Providing detailed information about missing animals, aiding in the swift recovery and reducing losses.

Incorporating this model into animal husbandry practices can significantly enhance the efficiency, accuracy, and overall management of the livestock, benefiting both farmers and the industry as a whole.

Related work:

Image recognition is a fundamental task in computer vision with a wide range of applications, and numerous studies have contributed to advancing this field. In this section, we review key research efforts that have shaped the landscape of image recognition and deep learning techniques.

Deep learning models have been used to classify and identify various animal species based on images [2]. These models often leverage large datasets of annotated animal images to train neural networks. They can be applied in wildlife conservation to monitor and track endangered species [4]. Beyond static images, deep learning has been applied to analyze animal behavior in videos. For example, researchers have used deep learning to track and identify individual animals within a group, monitor migration patterns, or study social behavior. Deep learning techniques have also been employed to classify animals based on their vocalizations [3]. This is particularly useful for monitoring and conserving species that are difficult to spot through visual means [2]. Deep learning models like Faster R-CNN and YOLO (You Only Look Once) have made significant progress in real-time object detection. These models are widely used in applications such as autonomous vehicles, surveillance, and robotics. Fine-grained object recognition focuses on identifying specific objects or species within a broader category. This is crucial in fields like agriculture (detecting plant diseases), biology (identifying specific cell types), and retail (identifying products).

VGG16, a milestone in deep learning literature, is a convolutional neural network architecture renowned for its simplicity and effectiveness [5]. Proposed by the Visual Geometry Group at Oxford, it features 16 layers with 3x3 convolutional filters, emphasizing depth for improved image recognition. While it excels in image classification tasks and has become a benchmark in the field

Proposed Dataset:

We have prepared primary dataset of Indian cows to train the CNN model to solve animal recognition problem. This dataset helps to identify specific cow through trained CNN model. There are some different traditional methods by which individual animal is recognized but few methods of these are temporary & painful for animal & could damage the animal permanently. To overcome these problems there are some automatic identification technologies which are useful but again there are some problems with this system, like animals can recognize using their specific colour pattern, iris print, muzzle print etc. but for this animal has to keep steady & calm at time of data collection & recognition process which is very difficult. So by keeping these problems in mind we have prepared this dataset to train CNN model for recognition purpose. Dataset is prepared by taking images of these four cows in different positions & posture.

To prepare this dataset we have selected 4 different cows from cow shelter among that 3 are the matured cows and one is the calf. We named these cows as cow1, cow2, cow3 and calf and similar classes are made in the dataset. These classes will be treated like the ids of the cow. Total 86 images are used to prepare the recognition dataset. Further the dataset is divided as

Train set and Test set. The size of our dataset is 157 MB. The count of images of cows are shown in the following table.

Class	Count of training images	Count of testing images	Total
Cow1	19	8	27
Cow2	19	8	27
Cow3	15	7	22
Calf	6	4	10
Total	**59**	**27**	**86**

Figure 1: The count of cow images in the dataset

Figure 2: Sample images of cows for proposed Cow recognition dataset

We have also use data augmentation approach like randomly crop technique since information for model training is limited. Figure 2 shows several examples of random cropping operations on dataset images.

Figure 3: Images generated in random crop operation

Experiment and Result:

The animal classification is very challenging task. The methods of animal recognition like RFID, muzzle prints, iris pattern and body pattern are discussed with their advantages and disadvantages. These methods are very useful for individual animal recognition. But here we are proposing the DL approach to solve animal recognition problem. We have used VGG 16 architecture to recognize the animal. The recognition task is carried out on the cow. We have taken four cows in which three are adults and one is calf. We have prepared the primary dataset of these cows to train the CNN model. In the dataset we have prepared four classes as cow1, cow2, cow3 and calf, these classes have the images of cows. These classes are stored in the folders called test and train. The cow1 and cow2 classes have 27 images of first and second cow respectively. The cow3 class has 22 images of third cow and the calf class includes 10 images of the calf. This bifurcation is given in the Table 2. The model trained on this dataset will be able to recognize the class of the cow. The cows selected for preparation of the dataset are different in body pattern, colour and size. These attributes makes them unique which would help the model in the recognition task.
We have trained the model on Google colab. For deep learning tasks, Google Colab is a great tool. It's an online Jupyter notebook that doesn't require any setup and includes a fantastic free edition that provides you free access to Google computing resources like GPUs and TPUs. Since the dataset is small for training the model we apply augmentation technique like random crop method. With this method the size of the dataset got increased and the model got the sufficient images for the training and testing. We have trained the model upto 1000 steps. The loss we received after the 1000 step is 0.05.

Result and Discussion:
The animal recognition is as important as human recognition. In the human recognition process the person is identified by using its unique features like iris print, finger print etc. In the animal case, we can use the same unique features to identify the individual animal like by using iris print, muzzle print body and colour pattern etc. But by using DL architectures we can achieve the same objective. So we took the problem of animal recognition and with the help of DL method we tried to solve that. We have prepared the primary dataset by taking total 86 images of four Indian breed cows. In the dataset two folders are prepared Train and Test, where we have kept 70% and 30% of images. The CNN model which we have used to solve the animal recognition problem is VGG16. We trained this model on our dataset upto 1000 steps on the Google colab environment. We have tested the trained model in the Google colab. The following figure shows the output given by the model.

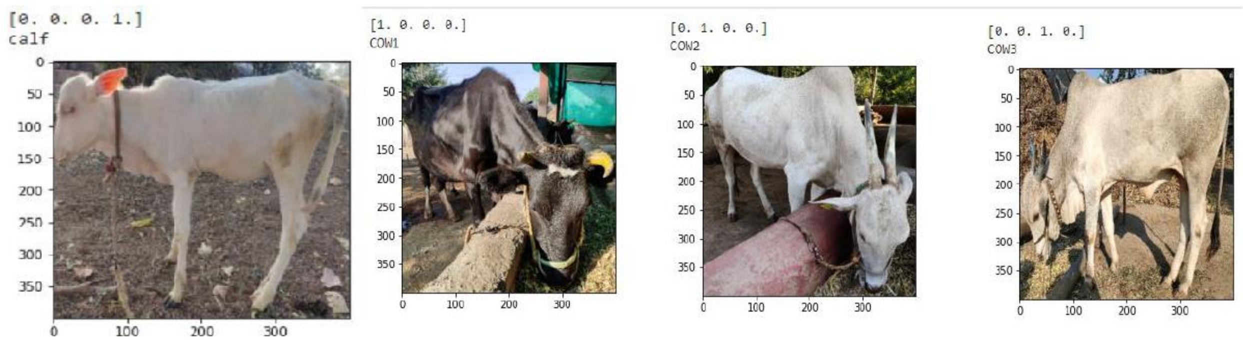

Figure 4: The recognition of cows of class1, class2, class3 and calf.

The model does not recognize the animal correctly all the time, there are some scenarios where model fails to recognize the animal.

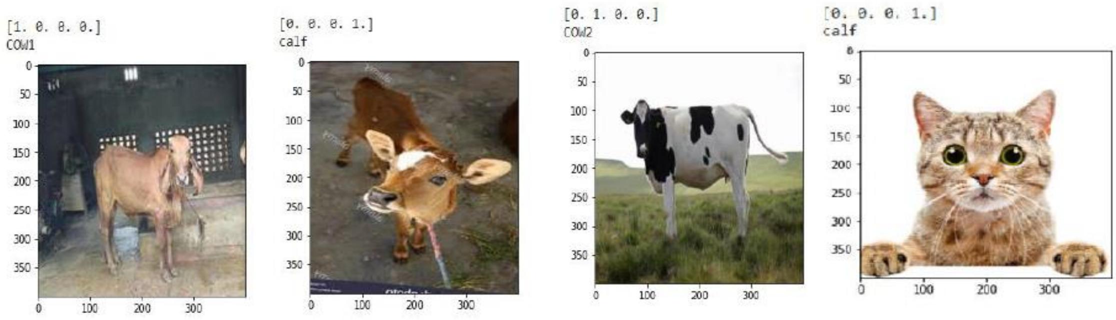

Figure 4: False prediction

This happens when model gets some similarities between the animals in the input image and dataset animals. The solution would be the number of images in the dataset can be increased and then the model can be trained on that dataset.

To get the accuracy of the trained model we gave 10 images of each animal to the model for recognition. Out of 40 images the model has recognized the 28 cows correctly hence the accuracy of model is 70%. The class wise accuracy is 70% for cow1 class, 60% for cow2 class, 80% for cow3 class and 70% for calf class.

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