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Animal Classification and Recognition Using Deep Learning

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***Abstract*— The dangers that animals now face have dramatically escalated over time. L live-animal marketplaces, animal-human disputes, animal-vehicle collisions, and other unintentional deaths as a result of inadequate animal monitoring are some of the serious risks to animals. An automated animal monitoring system that uses both animal detection and categorization methods is a dependable response to all of these dangers. In the paper, we propose a number of animal classification and detection algorithms that are targeted at various image modalities for a number of applications related to animal conservation. Initially, the "Convolutional Neural Network" (CNN), a method for classifying animal breeds, is shown. Then, we demonstrate various animal detection methods using various visual modalities. An autonomous ground vehicle-based livestock monitoring system called "EfficientNetB4" is suggested for the third image modality—fusion images. Using "EfficientNetB4", the system combines visual and thermal pictures. The proposed solutions handle a number of camera trap issues as well as difficult animal traits to ensure robustness.**

***Keywords*— wild animal dataset, convolutional neural network (CNN), EfficientNetB4, image classification.**

I. INTRODUCTION

One of Mother Nature's sentient and intelligent organisms is the animal kingdom. They were assumed as fundamental spiritual entities at the dawn of civilization. They contribute significantly to the stable upkeep of the ecological equilibrium. Each and every animal whether it is domesticated or wild, is essential to the food chain. Despite the fact that humans are directly dependent on animals, people have unfortunately brought the majority of animal species to the verge of extinction. Human Inhumane treatment of animals is beginning to backfire. The continuing Coronavirus pandemic gives strong proof for this. The epidemic in the novel is a karmic consequence of humankind's treatment of animals through the ages. The human race has hit snooze and is now debating the best way to prevent the spread of the new Coronavirus through the live-animal market.

Animals have been facing threats of many different kinds over the years. The most significant risks to wildlife include climate change, habitat degradation or fragmentation, culling, overuse of natural resources, pollution, and criminal activities like smuggling and hunting. A million or so species are listed as endangered in the 2019 biodiversity report, and many more are extinct every day. So, keeping an eye on animals is essential to preventing their extinction.

The technique of continuously observing the animals, their habitat, and their behavior, is known as animal monitoring. Animals are observed for conservation purposes as well as to prevent vehicle-animal collisions and animal-human conflict. The issue of animal detection is then addressed in the context of animal monitoring. Animal detection in advance can protect people from several attacks and mishaps caused by human-animal attacks and animal-vehicle collisions. Unreported occurrences in cattle stations, animal contraband into the live-animal market, the discovery of endangered animal species, etc. are a few more major issues that need animal detection. An effective animal detection system can assist in finding the animals and consequently save them in any of these situations. Animal detection, on the other hand, isn't always enough because, in some situations, it's necessary to appropriately classify the creatures. If a Black Panther were mistakenly identified as a cat by an animal intrusion detection system at a village boundary, for instance, the results could be terrible for both people and nonhumans. This illustrates how some animal species share striking inter-class similarities, like in the instance of the Black Panther and cats that are black in hue. Classifying these creatures is a challenge for fine-grained classification (FGC) because they resemble one another so closely. A system for fine-grained animal categorization is as essential as an animal detection system in the scenario described above. Using a bounding box, the animal detection method identifies animals after detecting them in images or recordings. Several methods have been used to detect animals, including Light .

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CBIR (Content-Based Image Retrieval)[1] Detection & Ranging (LID) [2][3] texture descriptor [4] Animal face detection [5]motion of animal adaptive Threshold Segmentation [6] threshold segmentation [7] Only static backgrounds—which are frequently absent—are suitable for motion-based animal detection and threshold segmentation. On the other side, the adaptive threshold segmentation makes a lot of false detections and improperly recognizes other moving objects, as animals. Since animals cannot see the camera and so cannot pose for identification, face recognition is not a reliable tool for animal detection. The animal may be found using the texture descriptors method, which compares the animal's texture to a previously established database. But, this method is only effective when there is only one kind of animal present and little background distraction. When the database is large, the content-based retrieval approach has poor searching performance. When dealing with a large database, the content-based retrieval algorithm's querying performance worsens. CNN [8] is widely credited for ushering in the current era of machine learning models. Moreover, animal detection systems began to perform better using transfer learning, even with little datasets[9]. The method of feature learning selected is crucial for a real-time application like animal identification. The majority of CNN-based models have the common flaw of having been trained using supervised learning methods, which are unsuitable for real-time applications since they cannot adjust to unlabeled classes[10].Moreover, since it is impossible to validate the results, real-time applications cannot rely on unsupervised learning methodologies. There aren't many unsupervised learning models in the literature, and those that are available have poor accuracy. Semi-supervised learning techniques were presented to fill the gap between these two approaches [11].

ML is a subset of AI(Artificial Intelligence) that enables the creation of mathematical models from data samples in order to generate predictions or decisions. Training data and test data, which may be labeled or unlabeled, are separated from sample data, with more data resulting in a more accurate prediction. Strategy for machine learning using massive amounts of data necessitates high computational capacity and extensive training time.

II. Related Wordage Layout

Gabriel S. Ferrante et.al (2022) Animals of all sizes are killed on Brazilian roadways at an annual rate of roughly 475 million.

Identifying, monitoring, and ensuring the protection of animals in high-risk areas necessitates the development of new systems and technologies, which governments cannot afford to develop given the magnitude of the problem. There are existing databases regarding animals in the literature on computer vision, but they do not specifically target the species that are most often involved in vehicular accidents. Therefore, the purpose of this study is to provide a novel dataset of labeled photos called the BRA-Dataset, which tries to fill this need. This identification of the five most fatally injured medium and large animals on Brazilian roadways may be used to train future animal detection programs. The dataset includes 1823 photos labeled in the PASCAL VOC format and YOLO Darknet, all of which were collected using the suggested acquisition technique and then manually cleaned. Experiments were also carried out on the BRA-Dataset to verify its efficacy in training and testing YOLO models. Without any further data or application process improvements, the findings demonstrated a high average accuracy reached over the initial dataset[12].

Xun Long Ng et.al (2022) The study of animal behavior has many practical implications. Existing animal behavior datasets, however, have some drawbacks. These include a lack of diversity in animal classes, data samples, and tasks offered, as well as in environmental circumstances and human observers' points of view. Animal Kingdom is a big and varied dataset designed to help with these gaps by providing a number of annotated activities that may be used to better understand animal behavior in the wild. The collection relies on the film of wild animals shot several times of day and in a wide variety of locales with varying backdrops, perspectives, lighting, and weather. To be more specific, their dataset contains 50 hours of annotated videos for the video grounding task, which aims to identify relevant segments of animal behavior in long videos, 30K video sequences for fine-grained multi-label action recognition, 33K frames for pose estimation, and 850 species spanning 6 major animal classes. This difficult and extensive dataset could help researchers test and improve cutting-edge techniques for studying animal behavior. They also provide a CAR(Collaborative Action Recognition) model that can learn both species-specific and generic features for action recognition with novel animals. They report encouraging results from their studies using this approach[13].

Zhang Song et.al (2022) In this article, they use neural networks to try to categorize 10 animal pictures. The categorization model's dataset is drawn from hundreds of online animal maps that have been pre-processed using artificial intelligence. Iconography heavily relies on convolutional neural networks since they are so effective at classifying images. This article examines the effect that adjusting various algorithm parameters has on the model as a whole. They analyzed the network topology and used that information to tweak the model in various ways to make it more suitable for classification tasks. Over 85% accuracy is achieved in the final training, with text precision hovering around 75%[14].

Dmitry Yudin et.al (2019) There hasn't been a lot of work done recently on the problem of spotting large animals in photos that include roadways. For this purpose, there are surprisingly few dedicated data sets. The onboard vision systems of autonomous vehicles require road sceneries, yet despite the prevalence of photos of large animals in popular open data sets, these rarely match. COCO datasets and Using Google Open Images, the research describes how such a specialized data set was compiled. The final dataset includes over 20,000 photos of large animals across 10 categories: "Fox", "Bear", "Horse", "Dog", "Elephant", "Goat", "Sheep", "Zebra", "Cow", and "Giraffe". The study investigates deep learning strategies for detection. The authors used state-of-the-art RetinaNet, R-50-FPN, YOLOv3, R-50-FPN, Faster R-CNN, and Cascade R-CNN R-50-FPN neural network architectures for training and testing purposes. They compared the methods by calculating their mean average accuracy (map) at IoU50% and their speed for 640x384x3 input tensors. Using an NVidia Tesla V-100 32GB graphics card, the YOLOv3 architecture has been shown to achieve over 35 frames per second while detecting ten classes at 0.78 mAP and one combined class at 0.92 mAP. The RetinaNet R-50-FPN architecture identified over 44 frames per second with a 13 percent reduced mean absolute precision (mAP) using the same hardware. PyTorch and Keras, two DL libraries, together with NVidia CUDA technology, were used to realize the software implementation. For instance, onboard vision systems of autonomous vehicles or driver-assistance systems could utilize the proposed data collection and neural network approach to animal recognition on photographs[15].

Daegyu Choe et. al (2020) Training a CNN effectively requires a substantial amount of training data and processing power. Complex network modeling and sample data collecting may be challenging in certain real-world contexts. An animal image transfer learning classification strategy is developed to enhance the convolutional neural network's classification accuracy and fitting speed. The fully connected layer of the pre-trained ResNet18 network is utilized to fine-tune the network model for the animal-10 dataset on Kaggle (eight animals). The generated network model has maximum accuracy of 97 percent for the classification of a particular animal and an overall accuracy of 92 percent for animal classification. In terms of fitting speed and accuracy, this type of transfer learning network model substantially outperforms its untrained counterpart. Because of their dwindling numbers, endangered species need to have their precise habitat distribution mapped out. In this research, a system was developed using a deep learning module to automatically gather, analyze, and store images of endangered species. The approach solves two issues encountered in earlier research while providing an alternative to manual picture classification. To begin, the probability distributions of response candidates were computed in those experiments, even if the correct answer did not exist within the group. This led to the suggestion of erroneous replies. Second, just one of more than two objects in each picture was selected for closer inspection. They used a special method for locating objects (YOLO) to fix the issue. Their technology is able to analyze 13 frames per second and has an average recall rate of 93.23 percent and an accuracy of 86.79 percent[16].

Rajasekaran Thangarasu et.al (2019) The spread of information on tracking the movements of wild animals is crucial for their protection. One of the most popular methods for wildlife monitoring is the employment of video traps, which are set up in strategic locations and go off automatically when an animal is detected. The aim of this research is to compare the performance of many machine learning algorithms in a categorization task. These methods range from the more traditional Support Vector Machine (SVM) to deep learning models like Alexnet and Inception V3. It has been shown that deep learning models can get better results than machine learning techniques. In this study, they take a step back and look at the big picture, comparing the performance of machine learning and deep learning models.

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Experiment findings indicate that InceptionV3 outperforms SVM, Random Forest, and AlexNet and that extremely accurate classification may be accomplished given sufficient data and well-honed approaches. The experiment evaluates the models' efficacy using the KTH dataset, which contains 19 types of animals. Twelve of these classes are used in the experiment [17].

Thirupathi Battu et.al (2023) In the field of animal identification, particularly with regard to predator species, not many successful approaches have been established. They provide a trustworthy method for learning to classify animal pictures taken with a camera trap in densely populated, noisy environments. They proposed two unique network designs for handling noisy labels; one used a clean sample, while the other did not. Using k-means clustering, they create subsets of the training data that have common characteristics. The clusters are then applied to the training of new networks. These more diversified networks are then used to collectively forecast or correct sample labeling by voting on the best results. The proposed technique was tested using two open camera-trap picture datasets, Panama-Netherlands, and Snapshot Serengeti. Their findings reveal that their method outperforms state-of-the-art approaches for identifying species from camera-trap photographs with high levels of label noise[18].

III. SIMULATION

A. Data Description

With some of the images coming from our photographs, we gathered the animal images from other websites. The UOM 50 Animal Image Dataset, which may be found at animals10, contains 5000 photos of 50 different animal species, with 100 samples in each class. The majority of the animal classes we have taken into consideration are found frequently in our country, and some of the species come from other regions of the world, such as Africa and Australia. While developing the dataset, we took into account a number of difficulties, including scaling, expansive views, and varying light. Our dataset was quite difficult because of intra-class diversity and inter-class similarity images. When trying to categorize animals, segmentation is a major obstacle. Their data takes into consideration the prevalence of animals, particularly wild animals, in the backdrop. their data collection also includes animals in a wide variety of poses.

Class No.	Animal	Class
1		Aardvark
2		Aardwolf
3		Bear
4		Bison
5		Black Panther
6		Buffalo
7		Bull
8		Camel
9		Cat

Figure 1: Sample Data of Animal Image Dataset

Category	Labels
'cane',	0
'cavallo'	1
,'elefante'	2
'farfalla'	3
'gallina'	4
'gatto'	5
'mucca'	6
'pecora'	7
,ragno	8
'scoiattolo'	9

IV. PROPOSED METHODOLOGY

A. Encode the dataset

This method of categorical data encoding (no order) is used when the attributes are extremely minor. With a single hot encoding operation, we generate a new variable for each tier of a category's feature. For each class, binary variables with the values 0 and 1 are used. Zero indicates that the category does not exist, whereas one indicates that it does.

Image resizing=224,224
Conversion to BGR2RGB image

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B. Dataset splitting

The Train Dataset is divided into training and validation datasets.

Training dataset (80%)
Testing dataset (20%)

C. CNN

When qualities are very minor, we resort to this method of categorical data encoding (no order). With a single hot encoding operation, we generate a new variable for each tier of a category's feature. Each of the classes utilizes binary variables with the values 0 and 1. Zero indicates that the category does not exist, whereas one indicates that it does.

We presumed the CNN architecture, which creates a probability map picture using a full image of the dataset as input. Three convolutional layers in our model will handle the 2-dimensional matrices that make up the input images. Figure 3 depicts the proposed model's architecture, in which each of the three convolutional layers learns independently under strict monitoring. Additionally, this network contains Fully connected (FC) layers, which each have 1,164,547 parameters. The nation has been hit by a serious energy crisis due to its dependency on thermal resources, leading to extensive load shedding and a virtual halt in everyday activity. [19]. The use of several nonlinear layers in DNNs is a common definition of deep learning. The combination of a deep neural network and an adaptive sunflower optimization algorithm (BLSTM-DNN-ASOA) is utilized to improve classification accuracy[20]. In this study, we employ the architecture of DCNN to recognize and label a variety of distinct animals [21]. A Deep Neural Network (DNN) is one type of Neural Network with more than 2 layers: an input layer, at least one hidden layer, and an output layer[22].

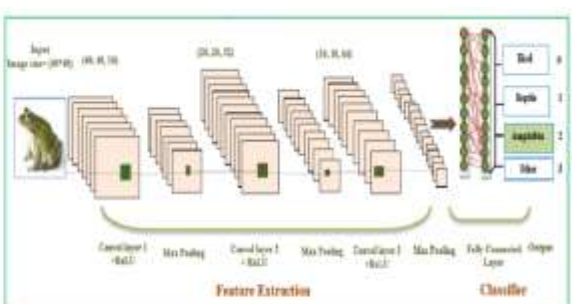

Figure 2: CNN architecture

D. EfficientNetB4

CNNs are frequently seeded with a limited set of resources and then expanded as more become available in order to increase accuracy. Increasing the number of layers in a CNN improves its accuracy. Adding more layers is only one way a network may expand. Randomly expanding the depth or breadth of a CNN is one way to scale a model, while utilizing higher-resolution input pictures during model training and evaluation is another. Some approaches enhance precision while others need tedious manual adjustments and provide mediocre results at best.

In our recent paper "Efficient Net: Rethinking Model Scaling for CNN," we demonstrate how a compound coefficient may be used to improve the scalability of convolutional neural networks (CNNs). Whereas the conventional approach arbitrarily modifies network properties like breadth, depth, and resolution, our approach scales each dimension evenly by using a fixed set of scaling coefficients. We have developed a family of models known as EfficientNets that beat current accuracy by approximately ten times (smaller and faster), thanks to recent developments in AutoML and our novel scaling method.

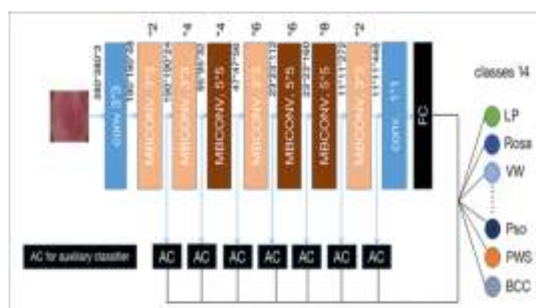

Figure 3. Basic EfficientNetB4 architectures

E. Training and Test Data

To create new data for training, validation, and testing, data augmentation is used. Since it is uncommon for a training procedure to provide optimal results with only a single dataset, we supplement it with additional information. As an outcome of these actions, the dataset grows since more photographs are now available due to the fact that several photos can be created from a single image. The Convolutional 2D layer has a tiny matrix called a kernel. Some tasks that it can complete include sharpening, edge identification, and blurring.

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A kernel convolution with the query image to accomplish this. The result is produced utilizing extracts from the layer before. The number of input channels is increased using convolution layers.

F. Running the Model

There were many pre-trained deep-learning models available. The EfficientNetB4 architecture is one of those that is implemented when a first sequential model is developed. There is synchronization between EfficientNetB4 and the model. There are currently no superior computer vision models. In place of a large variety of hyper-parameters, EfficientNetB4 made use of a 3x3 kernel with stride one convolution layers. These layers shared the same padding and max pool layer with a pair of 2x2 stride two kernels, which in turn used the same padding and max pool layer. In this design, the convolutional layers and the pooling layers are ordered in a manner that provides sense across the entirety of the structure. After the two entirely linked layers, data is generated using the soft-max algorithm.

V. RESULT OBTAINED

Due to an early halting callback, the training session ended after seventeen epochs. Overfitting has caused the validation accuracy to vary while the training accuracy has kept on improving. Only six of the sixteen epochs were run to prevent overfitting. Even though the Adam optimizer only operated for six epochs as opposed to the usual seventeen, the outcome was the same.

HyperParameters Setting:
Loss function =Categorical-Crossentropy
No. of Epochs = 6
Optimizer = "adam"
Batch size = 16

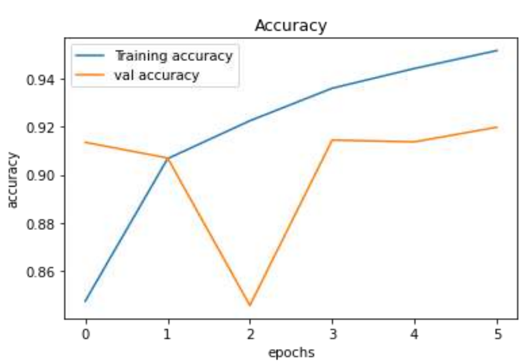

Figure 4: The Accuracy of Training and Validation is shown in the graph.

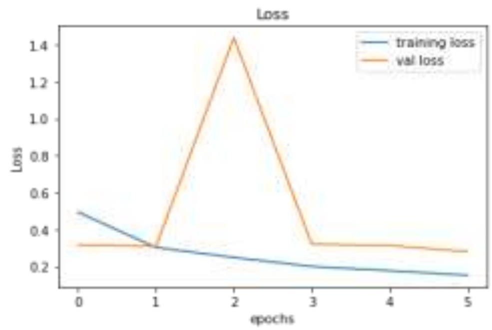

Figure 5: The graph shows the loss for Training and Validation

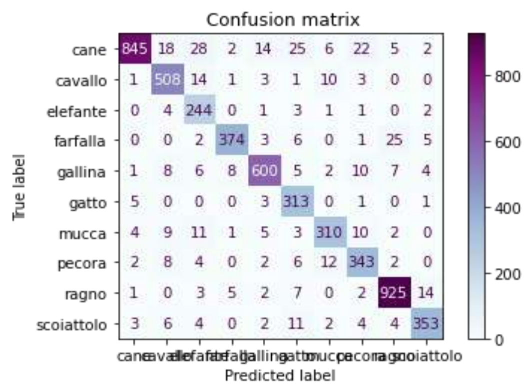

Figure 6: Confusion matrix

To demonstrate the model's reliability, one could use a confusion matrix. Visualizing both true positives and negatives and false positives and negatives facilitates an evaluation of the accuracy. This allows for an evaluation of performance. Figure 6 depicts the confusion matrix of the EfficientNetB4 design. Fig. 6 depicts the results of numerous example images. With an accuracy rate of above 97%, all of the test images were categorized properly. Fig. 6 displays some sample model results.

Model	**Training AUC**	**Training loss**	**Test AUC**	**Test loss**
EfficientNetB4	0.9728	0.0865	0.9198	0.2811

VI. CRITICAL ANALYSIS OF RESULTS

We also built the project using convolution and layer pooling rather than transfer learning. Figure 5 provides a schematic overview of the model. Here, the model's accuracy has dropped when compared to the one trained by transfer learning. Fig. 5 displays the rate of success and the rate of failure as a function of time.

With an accuracy of 97%, our model outperforms all other pre-trained networks in the industry. Deep learning techniques are used for animal species classification and labeling. The accuracy was improved by training bottleneck characteristics and transfer learning. The four architectures are trained using the dataset. EfficientNetB4's learning curves were a little bit difficult, but it had a 97% accuracy rate. With 97 percent accuracy, EfficientNetB4 is in the third position, followed by resnet50s with an 86 percent error rate. The pre-trained network outperforms the model built without one in terms of accuracy, according to studies that contradict each other.

VII. CONCLUSIONS

For the purpose of maintaining records of wild animals and ensuring their conservation, effective and regular monitoring of wildlife in their natural habitats is essential. Also, it aids in management decision-making. The traditional method of manual observations, on the other hand, requires more labor during the process and is more expensive. As this study's findings demonstrate, there are numerous methods for classifying and identifying animals. From the presentations of the various methods, we can conclude that the CNN classification strategy is the most effective for classifying animals, as it obtains high accuracy on the training dataset (97%) and the testing dataset (86%). Current developments in animal categorization often make use of convolutional neural networks (CNNs). In the future, it is anticipated that the algorithm will be enhanced to precisely identify the photos and also the accuracy.

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