

Efficient Wildlife Species Identification Using Deep Learning: ACNN-Based Approach

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ABSTRACT: In order to protect animals and address issues that arise when they encounter humans, we need less costly methods to learn about how animals behave in the wild. Although still and video camera monitoring is helpful, it often produces a lot of data that makes it expensive and difficult to look for specific species. This paper discusses a novel and cutting-edge method for identifying and differentiating animal-specific behaviors utilizing computer technology. We can do this by seeing pictures or videos. Our first objective was to differentiate between animals that are very similar, including tigers, leopards, and hyenas. Considering how similar tigers and leopards seem, this multiclassification task was very difficult. Using a dataset of enormous pictures of wild life animals in the forests and zoo. We created a deep learning model capable of accurately recognizing these species. With multiclassification accuracy rates of 98.05%, our deep learning models for automatic picture identification produced impressive results, demonstrating the efficacy of our methodology. We developed a new technique for locating creatures of interest in shifting habitats by including video footage into our approach, going beyond still photos. We believe that this is the first instance of this system being exploited in this manner.

Keywords: Wildlife, Deep Learning, ACNN-Based Approach, Convolutional Neural Network, ResNet convolutional model.

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Introduction

Recognizing and identifying animals is necessary for understanding population dynamics, how animals grow and develop by watching them at different times, analyzing how ecosystems work, and finding out what affects animal migrations. The species, appearance, biometric characteristics, behaviors, resource preferences, and significant environmental elements of an object can all be learned by a sophisticated computer vision system for object detection and recognition. The safety of the local fauna is ensured by these automated technologies, especially those employed for wildlife monitoring, which help to preserve ecosystems and their surrounding territories [1]. Animal ecology is now using big data and the Internet of Things. We can now learn a lot about wildlife populations thanks to advanced technology like satellites, drones, and devices that are on animals or in their environment. Researchers don't have to travel as far or as long to collect these data anymore, and people don't have to be in natural settings as much, which makes them less disruptive. There are now many AI tools that can analyze large datasets, but they are often too broad to study how wild animals behave and look in detail [2]. We don't know much about the amazing range of life forms that live on Earth with us. This group of animals may have the most different kinds of animals that have ever lived here. Sadly, people becoming engaged has hurt this diversity. Humans use about a quarter of Earth's resources to cultivate crops and rear livestock. Approximately one-third of Earth's land area is occupied by this. As a result, there are fewer natural systems and their varieties. To put it another way, since 1900, over 200 different kinds of animals with spines have gone extinct. According to the fossil record [3], species usually go extinct at a much slower rate than this.

Table 1. Estimated number of species on Earth [4]

KINGDOM	NUMBER OF SPECIES (OCEAN)	NUMBER OF SPECIES (TERRES TRIAL)	NUMBER OF SPECIES (TOTAL)
ANIMALS	2,150,000	5,620,000	7,770,000
CHROMISS	7400	20,100	27,500
FUNGI	5320	605,680	611,000
PLANTS	16,600	281,400	298,000
PROTOZO A	36,400	0	36,400
ARCHAEA	1	454	455
BACTERIA	1320	8360	9680
TOTALSPS	2,210,000	6,540,000	8,750,000

Artificial Intelligence Methods for Protecting Wildlife: AI has made many areas better. One of the industries that has gained the most from AI is the protection of animals. Because of AI in wildlife services, animals and people can now live together in their environments more peacefully. AI helps protect wildlife in five different ways [5].

Conventional Neural Network: Conventional Neural Network: To understand how a Convolutional Neural Network (CNN) works, think about how it sorts images. The CNN starts with a picture and uses several layers to find important features in it. These traits are then sent to one or more connected layers that figure out how likely each class label is. The predicted results are based on the class label that is most likely to be right [6]. When you think about how a Convolutional Neural Network (CNN) works, image classification is a good example. The CNN takes an image as input and passes it through a series of convolutional and pooling layers to find useful features. These features are then passed through one or more fully connected layers, which are in charge of classifying the data by giving each class label a probability. Then, the predicted output is the class label with the highest probability [7].

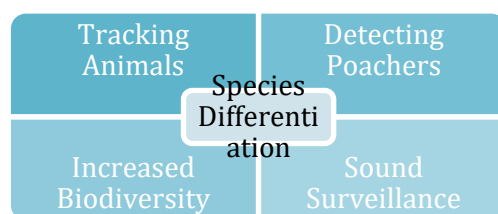


Fig 1: ways of AI in conservation of wild life

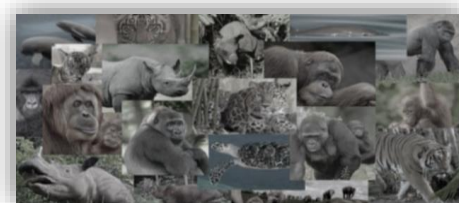


Fig 2: Endangered Species [8]

ResNet CNN: ResNet uses "skip connections" to handle neural networks with more than one layer [9]. The activation function output of one layer is added to the output of the subsequent layer via the skip connection. The network is split up into numerous residual blocks by this link, each of which contains two or more layers. The outcome is superior to or at least on par with its shallower counterpart thanks to these remaining blocks. The reason for this is that the weights can always be raised to get closer to the identity mapping [10], which claims that a shallow network performs at least as well as the residual block. The overall and a sample residual block are displayed [11].

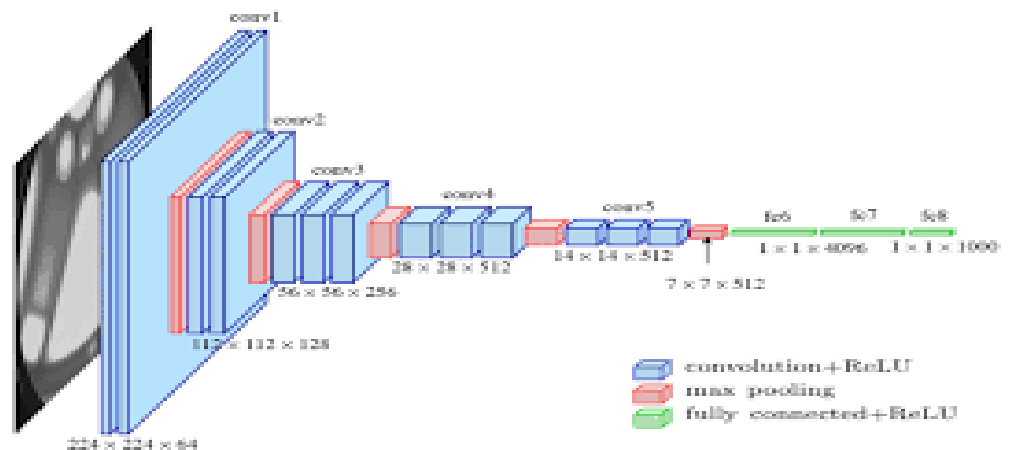


Fig 3: Systematic Diagram of ResNet CNN model [11]



Fig 4: Images contains labels

The Convolutional Neural Network (CNN) model is made to automatically learn and sort images by telling the difference between different types of animals. The CNN takes in each image and uses several layers to slowly pull out features that are unique to each animal class. These features include edges, textures, and higher-level patterns [12]. The experiment used a set of 2,700 labeled pictures of different zoo animals. Data visualization was essential for analyzing the dataset, validating label precision, and detecting visual patterns or anomalies that could influence model performance prior to training. This step made sure that the dataset was good for the detection task and helped us understand the input distribution better. The visualization function was used to show sample images with their class labels in order to give people a better idea of how the dataset is set up. To enhance learning outcomes, several systematic steps were integrated into the construction of the endangered wildlife detection model [13]. These processes required carefully changing training hyperparameters like the learning rate, batch size, and number of epochs, which have a direct impact on convergence and generalization. To prevent overfitting, an early stopping callback mechanism was added.

This stopped training as soon as the validation accuracy stopped going up. A history object that kept track of metrics like accuracy and loss over epochs made it easy to keep an eye on the training process and evaluate performance at every step [14].

Lastly, the training process's output showed that the model could make predictions, which was used as the basis for more testing and evaluation. All of these steps worked together to make sure that the CNN model was set up to accurately and effectively classify animal species, which helped with the bigger goal of finding endangered animals.

Results and Discussion

We made plots of accuracy and loss versus epochs for both the training and validation datasets to see how well the CNN models worked and where they may be improved. This picture of the model helps you understand how it works. The graphs show that the model got better during training.

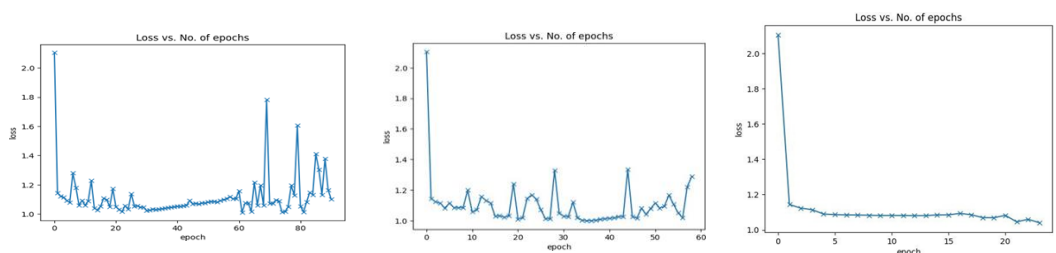


Fig 5: conception of Loss vs Epoch at 20,60,80 epochs in CNN

An accuracy vs. epoch plot shows how the accuracy of the model either rises or stays the same over time. This suggests that a high level of accuracy is being approached by the model. Model's accuracy is fair enough on the dataset.

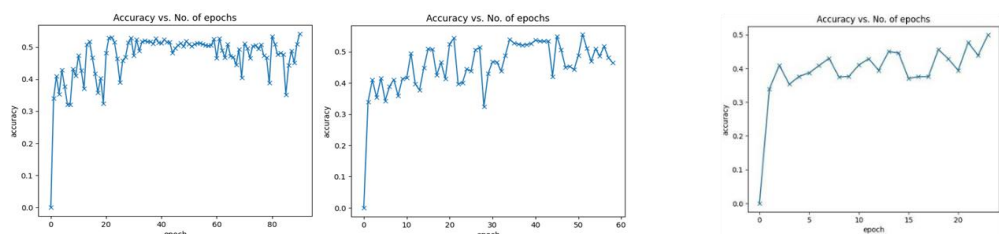


Fig 6: Accuracy Vs Epoch at 20,60, 80 Epochs in CNN

A graph that shows the accuracy and loss of the CNN training and validation datasets over time, with epochs on the x-axis. The goal of this was to see how well the model worked and find its flaws. These graphs show how the model got better as it trained. During training, you should always keep an eye on the model's output on the training dataset. We use the validation dataset to check how well the model works at the end of each training cycle by keeping track of its accuracy and loss. We also keep track of accuracy and loss data for each epoch. We make accuracy by using the values we recorded after training the model. By looking at a graph of accuracy vs. epochs, you can see that the model's accuracy either goes up or stays the same over time. It shows that the model's accuracy is getting close to a high level.

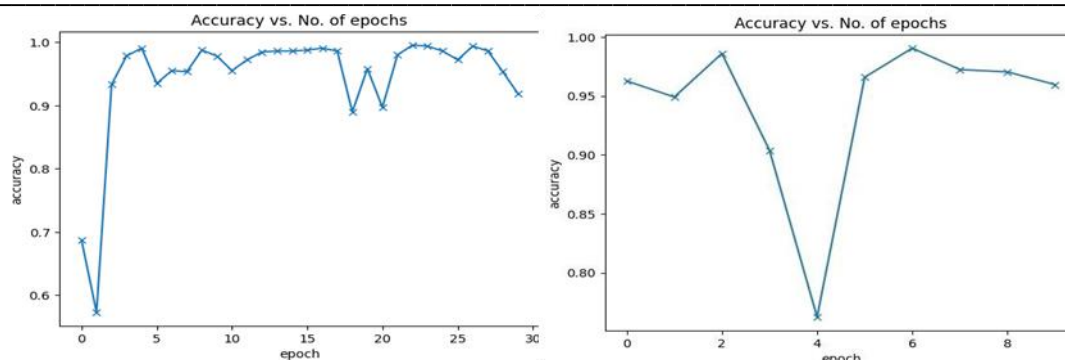


Fig 7: Accuracy Vs Epoch in ResNet CNN

Once model training is done, it is very important to test the model on the test set to see how well it works. A binary result is generated by estimating the model's predictions. According to the code, the model's accuracy on the test dataset is approximately 98.12%. This indicates that the majority of the samples in the test dataset can be accurately sorted by the model. The relative performance of the ResNet convolutional model with different numbers of layers and epochs and the wild life animal identification model with different numbers of layers and epochs is shown in the comparison table.

Table 2 : Model Evaluation Performance

Model	Epoch	Layers	Accuracy
CNN	30	20	87%
RESNET	30	19	98.12%

Conclusion

This study focuses on developing a system capable of detecting wildlife with an accuracy of 98.12% which involved constructing a robust dataset and potentially employing deep learning techniques to develop a neural network model capable of identifying various wildlife species. The model kept getting more accurate as it trained. This work has important real-world effects because it could be used for wildlife monitoring, anti-poaching efforts, research, teaching, and conservation. Improving accuracy even more and combining it with other technologies may be important areas of research in the future. When using this technology to monitor wildlife, ethical concerns concerning data security and privacy are also raised. Distinguishing between closely related species, such as tigers, leopards, and hyenas, was our primary objective. Because leopards and tigers have such similar appearances, this multiclassification test was quite challenging so created a deep learning model that can reliably differentiate between these species.

Author's Contribution: A.J Conceived the idea; A.R.I., Designed the simulated work and I.J.K., did the acquisition of data; A.J, Executed simulated work, data analysis or analysis and interpretation of data and wrote the basic draft; A.J, Did the language and grammatical edits or Critical revision.

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