

A Review On Image-Based Species Recognition Using Machine Learning

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Abstract — Primitive technology, including catching ink footprints on paper to distinguish between species by using different baits in the trap, has limited studies in animal species recognition. The goal of this project was to develop a species recognition system for traps based on eigenface identification. This method, which is typically used for human face recognition, is utilized to identify feral rodents like possums, cats, and weasels. The method exhibited success rates for identifying possums, cats, and weasels of 55%, 33%, and 45%, respectively, after eliminating the background from the training photographs.

Keywords — IMAGE-BASED RECOGNITION, SPECIES RECOGNITION, PROCESS, APPROACH

I. INTRODUCTION

Pattern classification has been one of artificial intelligence's most important research fields over the past few decades because of its crucial significance in a variety of applications of today's real world. Artificial intelligence (AI), also considered as machine smartness, is the intelligence displayed by a system as opponent to the natural intelligence exhibited by people. In the world of computer science, a "intelligent agent" is any machine that is capable of observing its surroundings and acting in ways that raise the possibility that it will be successful in attaining its objectives.

Machines simulate "cognitive" processes like "learning" and "problem-solving," which people typically connect with other human minds. When a computer mimics "cognitive" processes that people typically identify with other human minds, such "learning" and "problem-solving," the term "artificial intelligence" is employed.. The Animals Recognizer trains and recognizes the Animals using the photographs as input, as Deep Learning is often quite slower and difficult and also requires huge training data. The segregation of the animals is then made by their comparison how similar the creatures are to a template and the characteristics that were obtained. Experiments show our system can accurately identify a species of the animal after memorizing about 10 samples of that animal. The deep learning-based progressive foundation of the self-training makes it adaptable plus useful into variety of circumstances. Artificial intelligence (AI) research focuses on how the human brain thinks and solves issues.. This research also results in innovative software solutions. AI aims to improve computer capabilities in areas like problem-solving, debate, and education that are related to human understanding.

II. LITERATURE SURVEY

DEEPTHI K, VIMALA N, "ANIMAL SPECIES RECOGNITION SYSTEM USING DEEP LEARNING", International Research Journal of Engineering and Technology (IRJET), Volume: 08 Issue: 07 | July 2021

This focuses on the layer-by-layer processing of deep learning for animal species recognition. The accuracy of the outcome can be increased.

Kaitlyn M.Gaynor, Zhongqi Miao, “Insights and approaches using deep learning to classify wildlife”, NatureScientific reports, 31 May 2019

The cited paper describes research on insights and methods for classifying wildlife using deep learning, where it is examined if it is possible to categorize wildlife using deep learning by taking into account different deep layer techniques.

Margarita Favorskaya, Andrey Pakhirkaa, “Animalspecies recognition in the wildlife based on muzzle and shape features using joint CNN ”, Elsevier Procedia Computer Science, 2019

In order to confirm that animal species recognition is at least theoretically conceivable, this article looked at CNN algorithms.

III. EXISTING SYSTEM

There isn't a system in place that would allow for species recognition. A thorough investigation revealed that no system or product has been created that can reason and make decisions regarding the classification or recognition of species. In earlier developed approaches, machine learning or deep learning-oriented algorithms were not utilized. There were no appropriate tools for classifying or identifying species.

IV. PROPOSED SYSTEM

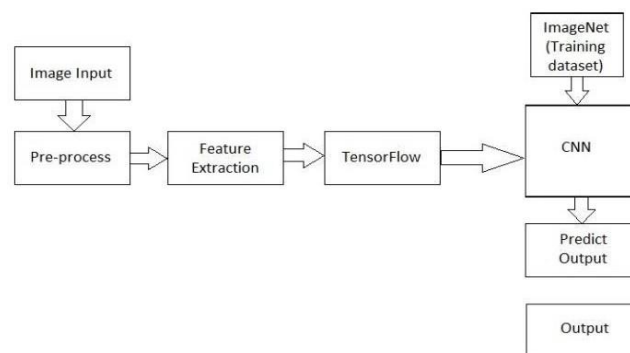


Fig.1 Block diagram of machine learning

As shown in Fig.1 initially, every user should upload an image first of the animal, including a along with animal which are habitual to earth.

The user's initial image must be taken into procedure during the pre-processing stage before being used for learning in order to enhance the image and enable precise prediction. The entire image is divided into smaller items, and each one's features are extracted. The obtained attributes are then converted into graph or pb(protobuf) values using Tensorflow. This conversion is required because the image is present in the ImageNet datasets as pb values. CNN compares the input data to the training dataset in order to accurately predict the animal type. Using a text-to-speech converter, the recognized animal species' output is changed to sound like a human voice.

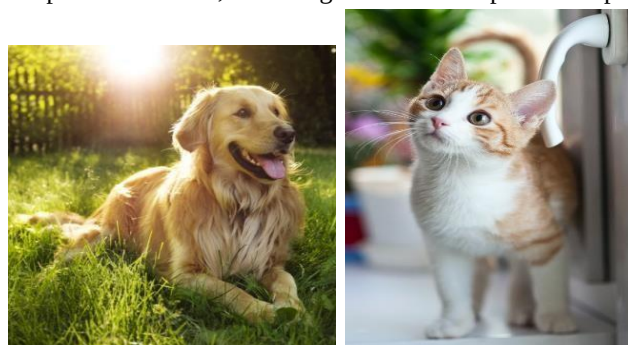


Fig.2 Sample image to feed in the dataset

The system is composed of two stages: Learning and testing. During the Learning span of time, a number of images are displayed as visual examples. During testing, a newly acquired image called as the testing image is as input. The knowledge gained during the training is then used to classify the test image into the most favorable category.

A. IMAGE INPUT

Having the test picture input: Those testing image are provided as input to the suggestion system, where they are converted into a pattern of binary tree. Test image's attributes are compared to those in the dataset's collection of previously categorized pictures in order to determine what kind of animal is being shown.

B. FEATURE EXTRACTION

The number of characteristics that are received as input for the test image can be decreased. This reduced amount of data, as opposed to the original, undisturbed data, may be used to achieve the desired purpose due to the selected characteristics may include significant data from the provided input. While low-level characteristics identify features in images and determine various degrees of representation, high-level features explain the data's more abstract attributes.

C. SPECIES CLASSIFICATION IN AN IMAGE

For a goal of classifying species, the similar output layer creates a likelihood that the animal recognized in the image belongs to one of the possible groups. Even though providing such a conclusion would minimize the time and effort needed to determine the best solution, species-specific It will be important to evaluate this theory with human competence.

METHODOLOGIES & CONCEPTS:

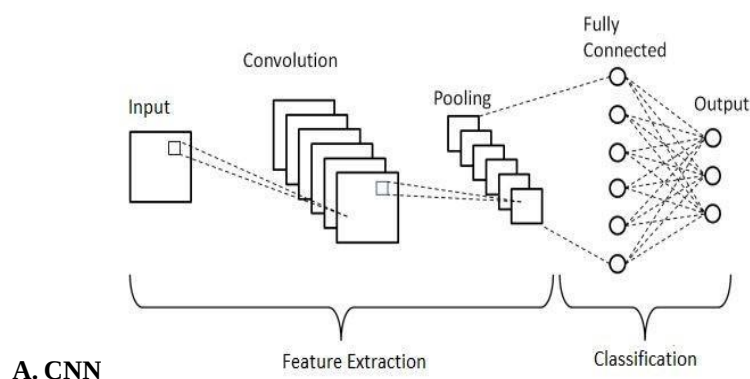


Fig. 3 CNN showing feature extraction and classification

When it comes to tasks like picture categorization, detection of an object, and recognition of an image, CNNs excel. The majority of the time, deep artificial neural networks are employed to classify images, group them according to the previous same things, and recognize animals in various scenarios. With the use of this module, a CNN will classify an animal image given its extracted features and subsequently identify the animal's species.

In a deep CNN, convolution layers use filters to apply to additional feature maps or the original image. To produce various activation characteristics for this layer, a collection of filters must be applied to the input image. Convolution layers and pooling are similar, but pooling serves a different goal. For example, Averaging brings the mean value into account throughout a region of filters, while max pooling selects the highest value. These layers are typically used to reduce the dimensionality of the network. The figure above demonstrates the usage of maximum pooling. A CNN's Prior to classification, the results are flattened using fully linked layers that are placed before the classification output.

B. KERAS

A robust and user-friendly Keras is a deep learning package for Python programming. We'll use this algorithm to build the CNN and apply this to solve the issue. Keras is easy-to-use but powerful deep learning package for Python programming. In this algorithm, we build a simple CNN with Keras and provide training it to tackle a real-world problem.

C. TENSARFLOW

This is a multipurpose and free library of software for many languages and flow of data. Using data flow diagrams, it is a free artificial intelligence toolset that creates models. It enables the construction of enormous, multilayered neural networks. The main applications of TensorFlow include classification, perception, comprehension, discovery, prediction, and creativity. In order to identify the animal species, the pre-processed species image will be converted into the values of graph.

D. TRADITIONAL COMPUTER VISION TECHNIQUES

Using handcrafted features extracted from images and machine learning algorithms for categorization are traditional computer vision techniques. These features may consist of shape-based features, texture descriptors, and color histograms. These features can be used to train the algorithms like SVM or any forests to categorize animal species.

E. TRANSFER LEARNING

Transfer learning makes use of pre-trained CNN models that were developed using sizable datasets like ImageNet. These models may be fine-tuned using a smaller, tagged dataset of animal species now that they have learned general visual attributes. Transfer learning can considerably boost the performance of animal species recognition by transferring the learned representations, especially when there are few labeled data points available.

F. DEEP LEARNING ARCHITECTURE

Other deep-learning architectures besides CNNs have been used to recognize different animal species. For instance, Sequential input can be analyzed using long short-term memory (LSTM) networks and recurrent neural networks (RNNs), such as animal sounds or behaviors.

Other architectures that have demonstrated promise in identifying fine-grained characteristics and variances in animal species include attention processes and capsule networks.

G. ENSEMBLE LEARNING

To create predictions, ensemble learning mixes different models. The accuracy and robustness of the animal species recognition system can be increased by using ensemble methods to train various models with varying topologies or initializations. You can use methods like bagging, boosting, or stacking to build an ensemble of models.

H. ACTIVE LEARNING

In order to minimize the labeling effort, active learning seeks to choose the most informative examples for annotation. Iteratively choosing a subset of samples from the unlabelled data, presenting them to experts for annotation, and then updating the model blends human expertise with machine learning methods.

I. DATA AUGMENTATION

By applying changes like rotation, scaling, flipping, or adding noise to the images, Using data augmentation techniques, the training data's diversity can be artificially increased.

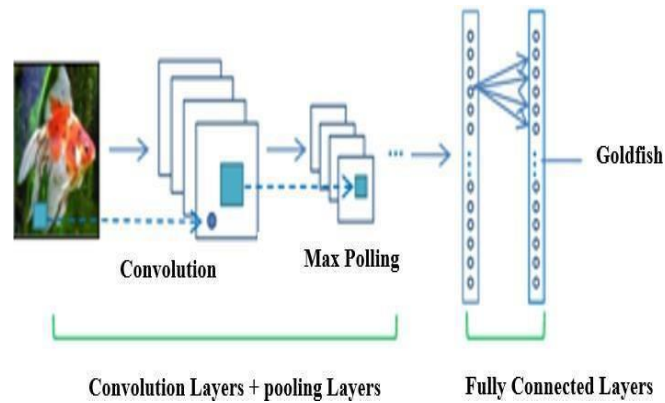


Fig. 4 CNN showing convolution and pooling layers

J. TRAINING AND DEVELOPEMENT

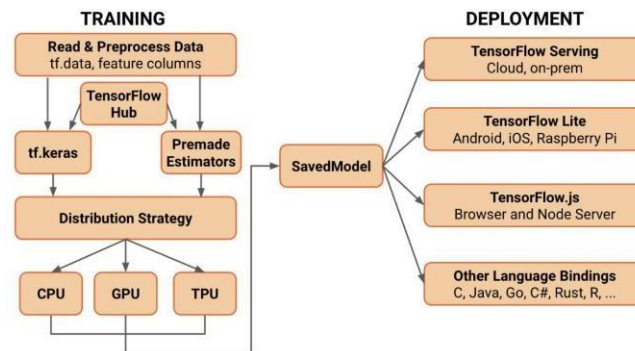


Fig. 5 Training and Development Flow

With the developments in deep learning and convolutional neural networks (CNNs), image-based animal recognition systems can actually attain high levels of accuracy. Due to their capacity to learn hierarchical features from images, CNNs have shown extraordinary success in image classification tasks, including the recognition of animals. The accessibility and effectiveness of the image-based animal recognition system also the quality of the training data. A diverse and To train a reliable and accurate model, you need a collection of animal picture labels. To guarantee that the model generalizes effectively to previously unseen photographs, the dataset should comprise images of numerous animal species in a variety of positions, lighting configurations, and backdrops.

Other variables that may affect the system's performance include the CNN architecture selected, the picture preprocessing methods employed (such as scaling and normalization), and the training optimization algorithms (such as stochastic gradient descent). It's crucial to remember that machine learning-based image-based animal recognition is still a developing field with room for advancement. To increase the reliability and precision of these systems, researchers and practitioners are constantly enhancing algorithms, creating larger and more diverse datasets, and investigating novel methodologies. Overall, machine learning-based image-based animal recognition has the potential to be a useful tool for automated species identification, assisting in ecological research, wildlife conservation, and biodiversity monitoring.

K. Key Advantages

- 1. High precision:** Machine learning models can now identify species from photos with astounding accuracy. CNNs and other deep learning architectures have proven to be capable of understanding intricate patterns and features from photos, leading to incredibly precise species detection..
- 2. Scalability:** Massive volumes of visual data may be processed rapidly and effectively by machine learning algorithms. The capacity to analyze big datasets encompassing many species thanks to its scalability enables

researchers to investigate and monitor various animal populations more efficiently.

3. Real-time identification: Real-time species identification of animals is possible with image recognition models, allowing for quick analysis and decision-making. This skill is particularly useful in situations like wildlife surveillance when quick identification is crucial for conservation efforts, and veterinary medicine to identify animal ailments.

4. Non-Invasive Monitoring: Traditional methods of species identification frequently call for cruel measures like animal trapping or tagging. A non-intrusive alternative, image recognition employing machine learning enables researchers to remotely identify and monitor animals, minimizing disruption to natural ecosystems.

5. Cost efficient: Machine learning models can process images at a reasonable cost once they have been taught. When compared to manual identification techniques and conventional field surveys, image recognition is more affordable, making it a practical option for animal species monitoring and study.

6. Accessibility and wide distribution: Many different devices, such as smartphones and cameras, can be used to implement image recognition models, making them available to a variety of users, including researchers, conservationists, and citizen scientists.

7. Automation possibilities: To continuously monitor and gather picture data, machine learning models can be combined with automated devices like camera traps and drones. As a result of this automation, less human involvement is required and animal species can be continuously observed throughout time, providing important insights into animal behavior, distribution, and population dynamics.

8. Possibility of data analysis and insights: Combining image identification with machine learning allows for the analysis of large datasets and the extraction of meaningful data. By analyzing patterns and trends in species distribution and behavior, researchers may advance conservation efforts, improve their understanding of ecosystems, and make data-driven decisions.

9. Versatility: A vast variety of animal species, from mammals and birds to insects and marine life, can be recognized by image recognition algorithms. Its adaptability makes it appropriate for a range of applications, including ecological research, wildlife protection, monitoring biodiversity, and studying animal behavior. Researchers and environmentalists may track the abundance and dispersion of diverse species in various environments because of this capability. Image recognition supports biodiversity conservation efforts by gathering and evaluating data on species' presence and abundance and delivering insightful data on ecosystem health and species diversity.

L.KEY APPLICATIONS

- 1. Biodiversity monitoring:** Image-based species recognition enables the design of targeted conservation strategies, such as habitat restoration projects, the establishment of wildlife corridors, and the implementation of captive breeding programs, all of which are aimed at protecting vulnerable species. Image recognition models can be trained to identify various animal species from images captured by cameras, drones, or other remote sensing technologies.
- 2. Animal behavioral research:** The examination of animal behavior is made possible by image recognition technology, which automatically recognizes and tracks specific people or species in pictures or videos. Animal behavior patterns, social interactions, mating habits, foraging tactics, and other ecological features can be studied by researchers. This knowledge broadens our understanding of animals. behavior, ecology, and ecosystem dynamics, contributing to the broader field of behavioral research.
- 3. Species protection:** For the purpose of identifying and keeping track of endangered or threatened species, image recognition is essential. These models can be used by conservationists to monitor population levels, evaluate the suitability of the habitat, and measure the effectiveness of conservation efforts.
- 4. Veterinary Medicine:** Applications for image recognition in veterinary medicine are useful. Veterinarians can detect numerous illnesses and ailments more precisely and quickly by looking at photos of animals. Image-based recognition might help in locating particular signs, patterns, or anomalies that might point to underlying medical conditions. Early disease detection and diagnosis can result in better treatment outcomes, lower morbidity rates, and increased animal welfare.

5. Education and outreach: To support educational initiatives like field guides, wildlife identification apps, and interactive learning materials, image recognition-based tools and applications can be created. The public's awareness, understanding, and involvement in species identification, conservation, and environmental stewardship are improved by these materials. People of all ages may identify species more easily and enjoyably thanks to image recognition technology, which promotes a greater awareness of biodiversity and the natural world.

V. CONCLUSION

There is a lot of room for development and new uses of image recognition in the identification and protection of animal species in the future. To fully utilize the potential of this technology, ongoing study, technological advancements, interdisciplinary collaborations, and careful consideration of ethical issues are essential. Image recognition will play a vital role in species monitoring, conservation initiatives, and our understanding of the natural world as it develops further. We can create the conditions for a more sustainable future for ecosystems and species by taking advantage of the opportunities and solving the difficulties.

REFERENCES

- [1] C. Geng, S.-J. Huang, and S. Chen. Recent advances in open set recognition: A survey. page 1–1, 2020. In *Proceeding of IEEE Transactions on Pattern Analysis and Machine Intelligence*.
- [2] DEEPTHI K, VIMALA N, “ANIMAL SPECIES RECOGNITION SYSTEM USING DEEP LEARNING”, *International Research Journal of Engineering and Technology (IRJET)*, Volume: 08 Issue: 07 | July 2021
- [3] Kaitlyn M. Gaynor, Zhongqi Miao, “Insights and approaches using deep learning to classify wildlife”, *Nature Scientific reports*, 31 May 2019
- [4] Margarita Favorskaya, Andrey Pakhira, “Animal species recognition in the wildlife based on muzzle and shape features using joint CNN”, *Elsevier Procedia Computer Science*, 2019.
- [5] S. DIVYA MEENA L., AGILANDEESWARI, “An Efficient Framework for Animal Breeds Classification Using Semi-Supervised Learning and Multi-Part Convolutional Neural Network (MP-CNN)”, *IEEE Access*, October 30, 2019
- [6] A. Khan, A. Sohail, U. Zahoor, and A. S. Qureshi. A survey of the recent architectures of deep convolutional neural networks. *Artificial Intelligence Review*, Apr 2020.
- [7] Ms. P. V. Amabtkar, Dr. R. S. Deshpande, “Interpretable Deep Learning Models: Enhancing Transparency and Trustworthiness in Explainable AI”, vol. 11, 2023.
- [8] Samrudhi Jayashri Kuware, Mr. Vinod S. Wadne. Enhance the performance of Cancer and Diabetes prediction by Techniques of Machine Learning. *IJEDR 2020 - ISSN: 2321-9939*. Vol. 8.
- [9] Deploy machine learning models on mobile and IoT devices. <https://www.tensorflow.org/lite>. Accessed: 2020-03-25.
- [10] L. Weng. Object Detection Part 4: Fast Detection Models. <https://lilianweng.github.io/lil-log/2018/12/27/>