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IDENTIFICATION OF ANIMAL SPECIES FROM ANIMAL FOOTPRINTS AVOID ENTERING DWELLING PLACE

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Abstract: With the goal of preventing unauthorized access into places where people live, this study offers a novel method for identifying different animal species based on their footprints. The suggested technique consists of a series of steps that include warning system, probabilistic neural network (PNN) classification, Canny edge detection algorithm, and picture processing.

During the first stage, footprints that are gathered close to places of residence are processed to improve their quality and extract pertinent information. Then the Canny algorithm is used to find edges and identify certain patterns in the footprints. These processed footprints are sent into the PNN, a powerful classification method that can identify complex patterns and reliably predict species.

Using a large dataset of known animal footprints, the PNN is trained to identify certain traits across different species. When a new footprint is seen, the PNN quickly examines its distinct characteristics and offers a species categorization. This categorization is then used to activate a warning system that notifies locals of the possible existence of a certain animal species close to their place of residence.

Homeowners may take preventative action and avoid unintentional interactions with wildlife thanks to this all-inclusive method that provides a proactive plan to reduce human-wildlife conflicts. This work promotes safety and upholds the integrity of both environments by using edge detection, machine learning, image processing, and real-time alerts to foster a happy coexistence between people and animals.

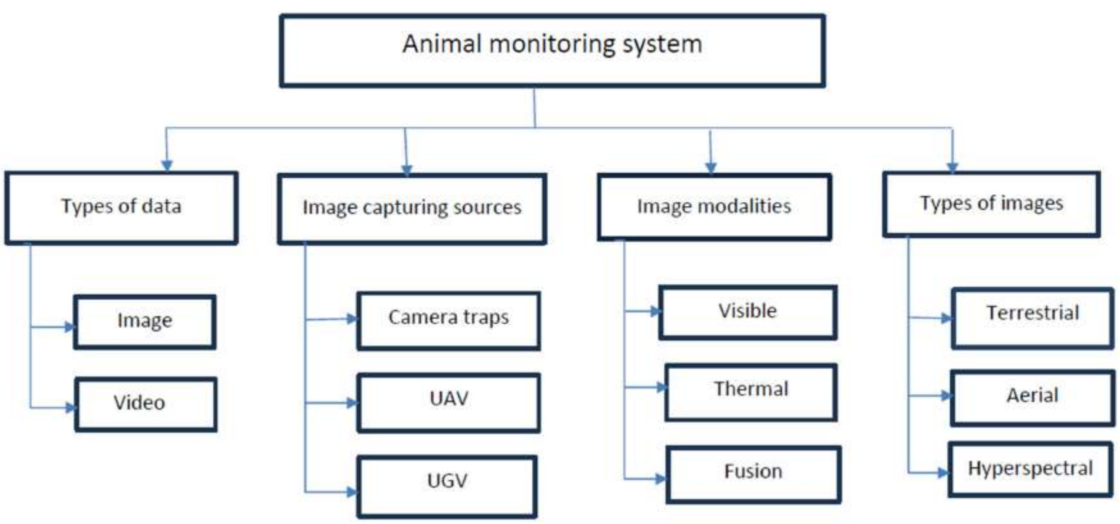
I. INTRODUCTION

Among Mother Nature's sensitive and intelligent creatures are animals. In early culture, they were revered as cardinal spiritual creatures. They are essential to the proper upkeep of the ecological equilibrium. Every animal in the food chain, domesticated or wild, has an essential function to do. Even while people rely directly on animals, the majority of animal species have unfortunately been driven to the verge of extinction by humans. The mistreatment of animals is beginning to backfire on people. The worldwide coronavirus epidemic now raging provides compelling evidence for this. The new epidemic is a karmic outcome of how people have always treated animals. At least from the live-animal market, where the new Coronavirus is thought to have originated, the human species has collectively pushed the snooze button and is now considering methods to preserve the animals. Animals have consistently faced dangers in a variety of ways throughout the years. The most significant risks are pollution, overuse of natural resources, culling, habitat fragmentation or loss, climate change, and illicit activities including smuggling and poaching. The 2019 biodiversity report states that around one million species are classified as endangered, and that several species go extinct on a daily basis. Therefore, keeping an eye on animals is essential to preventing their extinction.

mechanism for monitoring animals

The practice of continuously observing animals, their habits, and their surroundings is known as animal monitoring. Animals are observed for conservation purposes as well as to prevent animal-vehicle collisions (AVC) and human-animal conflict (HAC). The issue of animal detection is then addressed by animal monitoring. Animals may be protected against a variety of assaults and mishaps caused by HAC and AVC by being detected in advance. Unnoticed accidents at cattle stations, smuggling animals into the live-animal market, identifying endangered animal species, etc. are a few more major issues that need for animal detection. An effective animal detection system may assist in locating the animals in each of these situations, saving them in the process. On the other hand, there are situations in which precisely classifying an animal is necessary, therefore animal detection alone is not always enough. For example, if a village border's animal entry detection system misidentifies a Black panther as a cat, it might have potentially fatal consequences for both the animal and people. The key takeaway from this is that certain animal species, like the Black Panther and the black cat, show striking interclass similarities. The classification of these creatures is a Fine-Grained Classification (FGC) difficulty because of their almost identical appearances. In reference to the aforementioned example, an animal detection system is not as important as fine-grained animal categorization.

Numerous methods for monitoring animals have been developed by wildlife researchers, including satellite tracking with radio collars (Venkataraman et al., 2005), very high-frequency radio tracking, satellite-mounted video monitoring systems, GPS tracking, pyro-electric sensors, and wireless sensor networks (WSN). However, since these methods are mostly limited to a restricted geographic region, they have not been very successful. The camera trap technology has advanced and become more widely accessible to researchers due to the quick speed at which technology is developing. They have proven effective in a number of applications involving animal monitoring.



Animal monitoring system

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II. Literature survey

Using two CNN architectures—GoogleNet and LeNet—Hsu (2015) suggested an animal categorization model that yielded accuracy ratings of 90.5% and 91.1%, respectively. Later, an unsupervised learning technique for fine-grained recognition was presented by Yang et al. (2012). The algorithm recognizes shapes that appear often in every picture and uses them as templates. On the SD dataset, the template matching method has a 38% accuracy rate. Kanan (2014) further improves this accuracy by using Gnostic fields. The author created a shape-size invariant model that can handle animals of different sizes and forms using pattern recognition units and picture descriptors. Furthermore, the dataset's bias has no effect on the model. The model's accuracy has increased by 47%. Subsequently, Selective Pooling Vectors (SPV) were presented for the FGC issue by Chen et al. (2015). Using a threshold value determined by the quantization error, SPV converts the image descriptors into vectors and chooses the best ones. Additionally, an approximate non-linear function f that establishes the probability of categorization for the different dog breed classifications is obtained using the codebook as an approximation function. With the SD dataset, 52% accuracy was attained by SPV. Using NASNet-A and Inception-ResNet-v2, Raduly et al. (2018) suggested a multi-class dog breed classification model. The Google team created both architectures, however the former is based on Neural Architecture Search (NAS). The model proposed by Ahmed, A., Yousif, H., Kays, R., and He, Z., "Semantic region of interest and species classification in the deep neural network feature domain," Ecological Informatics Gavves et al. (2019) proposed a FGC model with alignments, and it achieved an accuracy of 85.27% and 93.86% on both architectures. The characteristics are retrieved from the photos after they are segmented and aligned automatically. Nevertheless, the accuracy of this model was 50.1%, and ad hoc alterations are needed in each of the separate components. Since the backdrop is uncorrelated and distracts from the classification objective, Chai et al. (2013) developed a fine-grained categorization model employing symbiotic segmentation for distinguishing the foreground from the background. Following segmentation, the model highlights the discriminative portions using part localization via human bounding box annotation. On the SD dataset, this supervised method had an accuracy of 45.6%. Simon and Rodner (2015) suggested an unsupervised part finding technique based on Neural Activation Constellations (NAC). The idea is to take use of the CNN channels by using the activation maps of deep neural networks. The neural network's activation maps will function as a part detector, allowing for the creation of a part model without the need for supervised bounding boxes. Weakly-supervised classification is subsequently used to extract the animal's discriminative pieces using the part model. Additionally, the NAC is a method of data augmentation. NAC obtained a 68.61% accuracy rate.

A unique fine-grained classification model based on recurrent neural networks (RNN) was suggested by Sermanet et al. (2019). At the beginning of RNN attention, the model pre-trains on a large-scale dataset and imposes an active visual network. With high-resolution attentions, the model can quickly determine the most discriminative area without any supervision. Furthermore, the model performs just as well on low-resolution photos with blurry fur patterns and face characteristics. The suggested RNN classified the dog breeds with an accuracy of 76.8%. In order to attain respectable performance and scalability, Krause et al. (2016) suggested a unique fine-grained recognition approach that makes advantage of noisy data. Two forms of noise are purposefully introduced by the model: cross-domain noise (such as photos of cats in dog classes) and cross-category noise (mislabeling cats as dogs). The authors use Inceptionv3 network for categorization and confidence-based sampling in active learning approaches for data collecting. The model's classification accuracy

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for Stanford dogs is 80.8%. In order to detect the local discriminative components of the animals, Liu et al. (2016) suggested a fine-grained identification model employing a Fully Convolutional Attention Network (FCAN), a kind of reinforcement learning technique. FCAN exhibits a quicker convergence when using the greedy reward method. The accuracy of the model was 88.9% on the SD dataset.

A bilinear CNN model was presented by Lin et al. (2020) for the fine-grained recognition challenge. Bilinear pooling, which mixes the pairwise local feature vectors, forms the basis of the model. On the SD dataset, the accuracy of this model was 84.10%. Eventually on, a pairwise confusion model for a FGC system was also suggested by Dubey et al. (2018). Using a unique optimization strategy, the model is trained using end-to-end CNN. To minimize overfitting, the model purposefully creates confusions in the neural network's activations. After that, the pairwise confusions are regularized to reach 83.75% accuracy and respectable performance. Multi-attention based CNN for fine-grained recognition model was suggested by Zheng et al. (2017). With the class labels, the model finds a discriminative or informative area. Eventually, a multi-attention neural network with multi-class labels was also presented by Sun et al. (2018). Thus, using a variety of channels, our model was able to learn many informative areas. Sun et al. (2018) obtained 85.2% accuracy, compared to Zheng et al. (2017) who reached 87.3% accuracy. A fine-grained recognition model with two essential elements—the diversification block and gradient boosting—was presented by Sun et al. (2019). These elements compel the network to detect even the smallest variations across classes with significant intra-class variance. The most notable qualities are emphasized by the diversification block, which also compels the categorization to make use of them. Conversely, the gradient boosting function is a loss function that addresses class ambiguity resolution. These two parts working together makes it easier for the network to identify the most effective characteristics. After extensive testing, the model's accuracy on the SD dataset was 87.7%.

For the FGC issue, Hu et al. (2019) suggested a poorly supervised data augmentation network. Through poorly supervised learning, the model use attention maps to determine which sections are the most discriminative. The photos are taught and enhanced by attentive cutting and lowering. In the first step, the model extracts discriminative characteristics; in the second stage, attention maps are used to find the precise positions of the animals. This results in improved performance. The accuracy attained by the model is 80.8%. An attentive paired interaction model was presented by Zhuang et al. (2020) for FGC. While previous models concentrate on highly discriminative characteristics, this model, in contrast to the models presented so far, attempts to learn the contrastive hints among the highly confused classes. Through continuous and recurrent learning, this paired attentive model picks up two fine-grained pictures.

III. METHODOLOGY

A set of computer algorithms known as "machine learning" is capable of self-improvement and learning from examples without the need for explicit programming. Artificial intelligence includes machine learning, which uses data and statistical methods to forecast an output that may be used to derive practical insights.

The concept that a computer can independently learn from the data (i.e., example) and provide correct results is the breakthrough. Bayesian predictive modeling and data mining are strongly connected to machine learning. The computer takes in data and creates replies using an algorithm.

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Making recommendations is a common machine learning problem. All movie or series suggestions for Netflix users are predicated on their past use history. Unsupervised learning is being used by IT businesses to enhance user experience via personalized recommendations.

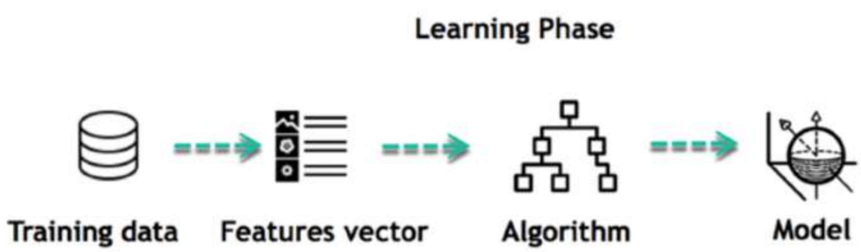
Numerous other functions, including as fraud detection, predictive maintenance, portfolio optimization, job automation, and so forth, also make use of machine learning.

How Machine Learning Operates

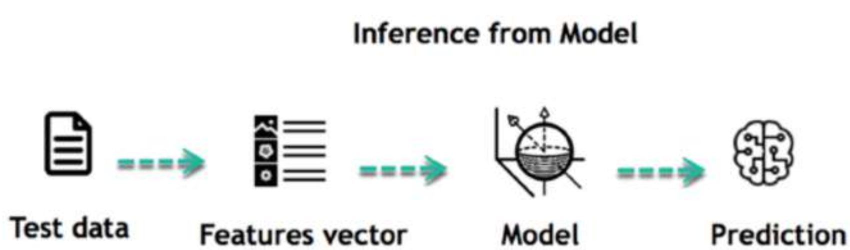
The brain that does all the learning is machine learning. Machine learning is comparable to human learning. Experience is how people learn. Predicting becomes easier the more information we have. By analogy, our chances of success are lower in an unknown circumstance than in a recognized one. Computers get the same training. The machine observes an example in order to produce an accurate forecast. The computer can determine the result when we offer it another example that is comparable. But much like a person, the computer finds it challenging to forecast if it is given a case that hasn't been seen before.

Learning and inference are machine learning's main goals. Initially, the computer gains knowledge by identifying patterns. The data is what led to this finding. Selecting the right data to feed the computer is an essential skill for a data scientist. A feature vector is a set of properties used to solve an issue. A feature vector may be seen as a subset of data applied to an issue.

The computer turns this finding into a model by using sophisticated algorithms to simplify reality. As a result, the data are described and condensed into a model during the learning step.



Learning phase



Inference from Model

IV. IMPLEMENTATION

Modules description

Data Collection:

Online database of animal tracking data hosted by the Max Planck Institute for Ornithology. It is designed to help animal tracking researchers to manage, share, protect, analyze, and archive their data. Movebank is an

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international project with over 11,000 users, including people from research and conservation groups around the world.

Pre-processing animal footprint images are converted into gray-scale. Gray-scale image is an image consists of binary contents in the form of 0 and 1 pixels of the initial rgb image.

Gray-scale image consists of image pixel is a single sample representing only small amount of light, it carries only intensity information between (0 to 1). The converted grayscale for further processing, it should be further reduced in information which includes edge detection.

Feature Extraction Module:

Here we choose Gabor filters for the purpose of feature extraction. Gabor filters effectively preserves the texture characteristics of an image pattern in frequency domain.

By applying the selective scale and orientation Gabor filter on an image where, the texture analysis is accomplished. Initially the images are segmented before extracting desired feature.

Classification Module

Classification After processing and feature extraction we have to determine the animal class by comparing the input image with trained data, trained data consists of 80 percent samples, probabilistic neural network is used for footprint classification.

Saving the Trained Model:

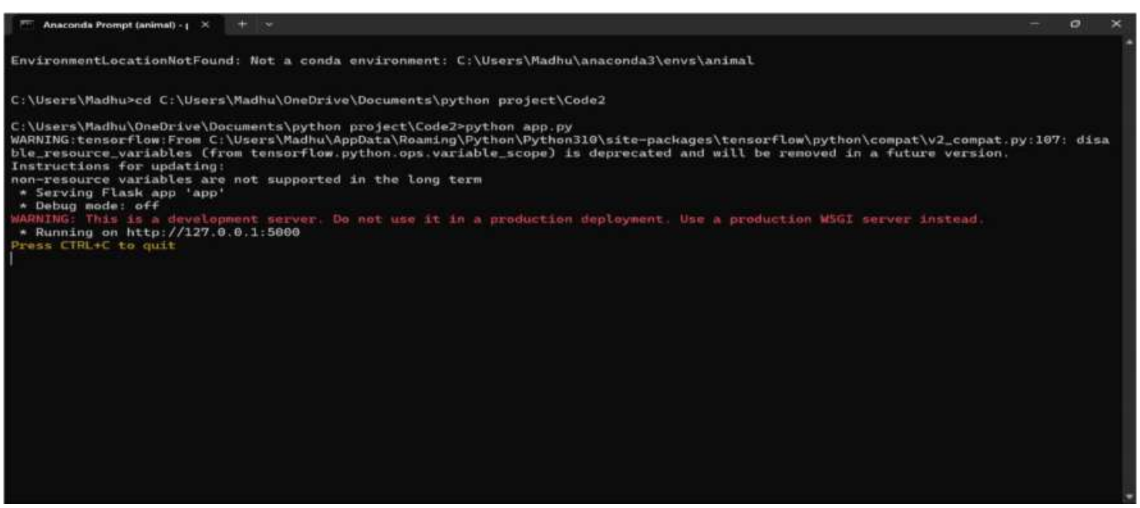
Once you're confident enough to take your trained and tested model into the production-ready environment, the first step is to save it into a .h5 or . pkl file using a library like Pickle.

Make sure you have pickle installed in your environment.

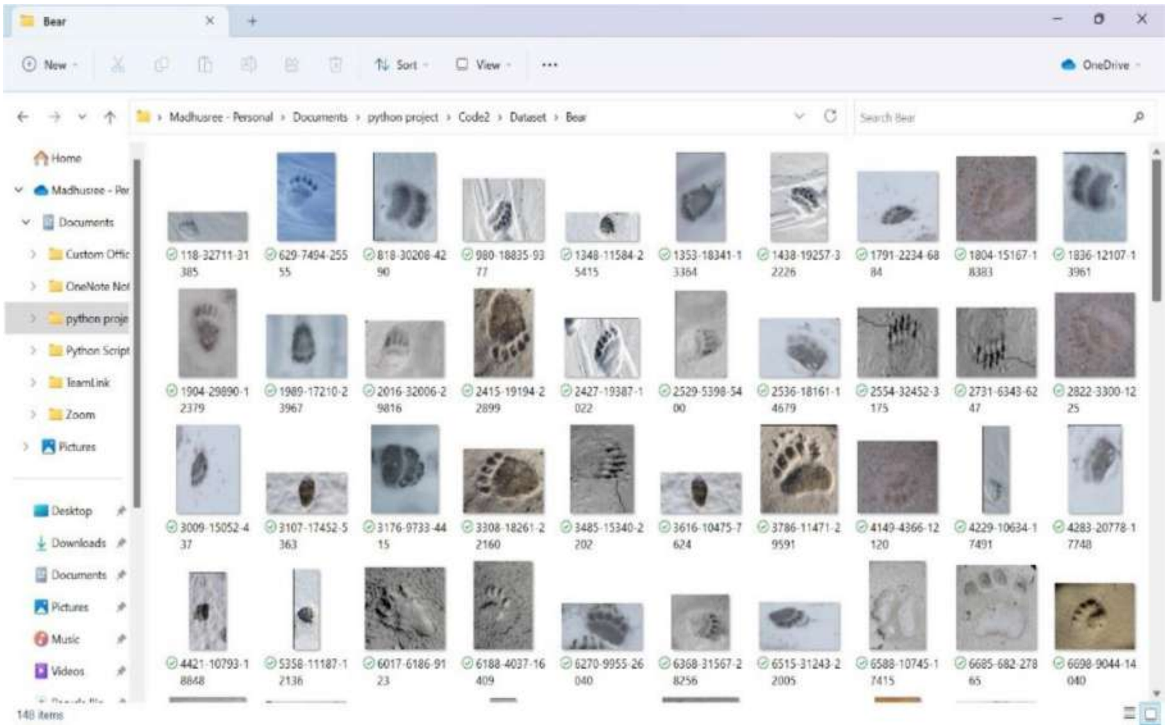
Next, let's import the module and dump the model into .pkl file

V. RESULT AND DISCUSSION

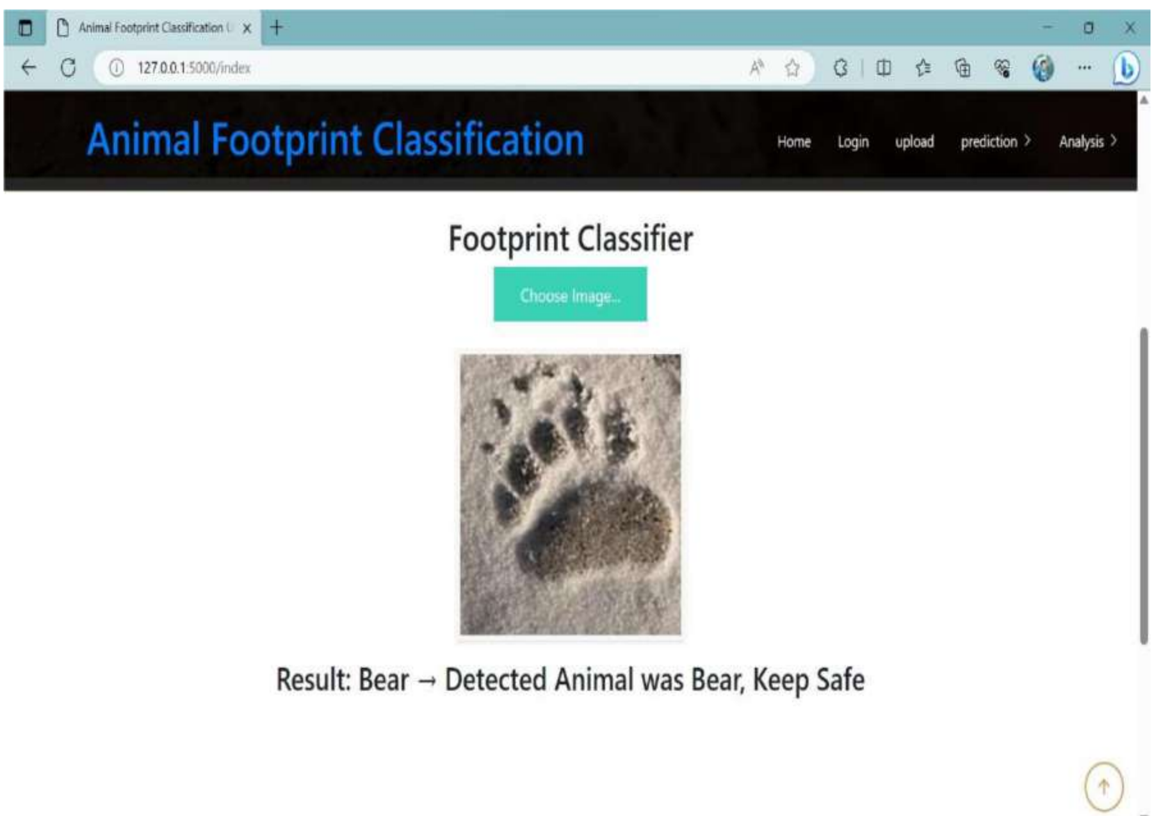
In this paper it includes the steps of operations and also discuss about the results of animal footprints which are gone through several processing and algorithm steps with a message and warning if humans have any risk



Anaconda prompt window



Bear Dataset



Bear footprint result

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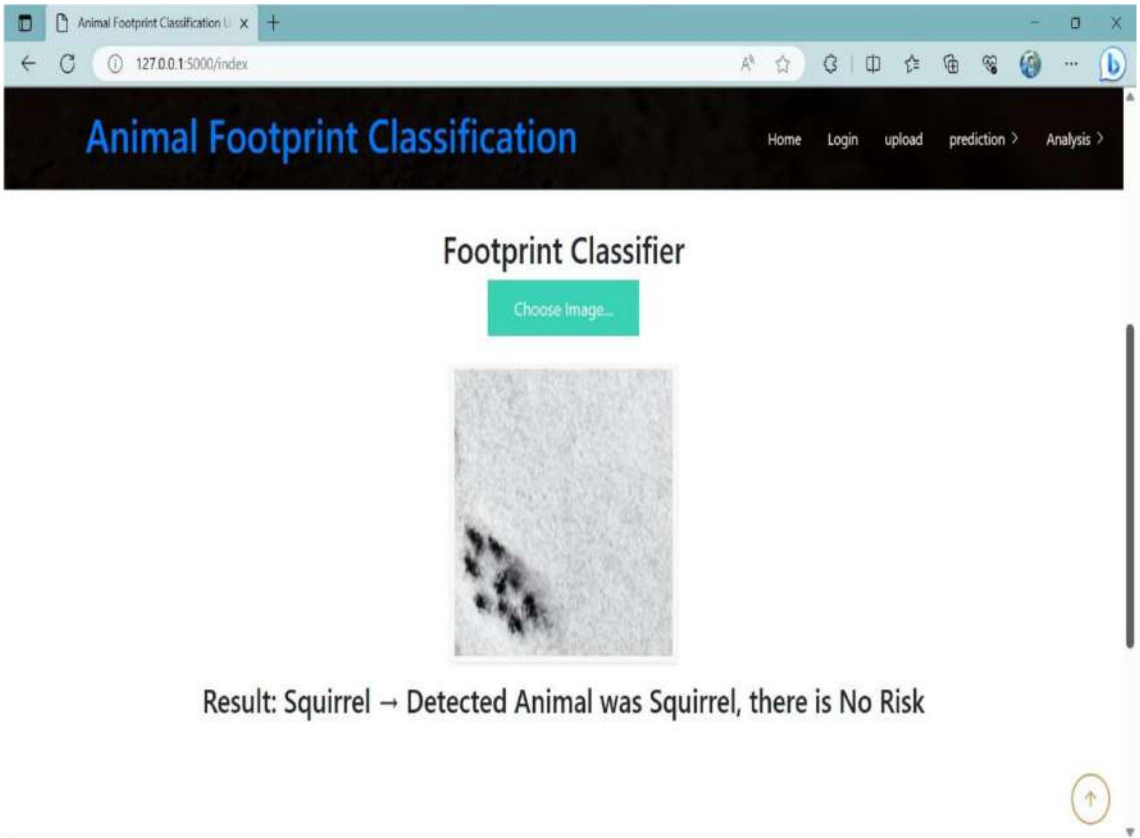

Squirrel footprint result

VI. CONCLUSION

In this article, we have looked at the procedures that need to be followed in order to get the results of the footprints, as well as the message that comes along with the identification of the footprint. The study offered a number of reliable and effective animal detection and categorization technologies that may be used to the field of animal conservation. Throughout the whole of the thesis, we have covered how animals are constantly put in risky situations regardless of where they are. The thesis also discusses applications such as HAC, AVC, livestock monitoring, and endangered animal species that call for an animal detection and classification system. These applications need to be able to identify and categorize animals. In addition, we have provided information not just on the continuing worldwide epidemic but also on how animals are related with the new coronavirus. All of these potential outcomes call for the implementation of an accurate animal detection and categorization system that is able to locate the animals in question and rescue them from the imminent danger. Following this, the thesis provided a number of different animal detection and classification methods that may be used for a wide variety of applications relating to animal preservation. As part of the process of monitoring animals, many different methods of animal categorization and detection were discussed. To be more specific, the thesis showed two effective fine-grained classification systems that made use of semi-supervised learning approaches, as well as three distinct animal identification systems that made use of three distinct picture modalities, namely visual, thermal, and fusion images. Moreover, the thesis included a discussion of how these systems may be improved. An animal detection and counting system that might monitor endangered animal species using aerial photographs was proposed using visible images as its primary source of data. For the purpose of livestock monitoring using an autonomous UGV fitted with multi-sensor cameras, another animal detection and counting method was presented utilizing fusion pictures. Using a FLIR e40 thermal imaging camera, we were able to acquire images of a number of different animal species and provide a suggestion for an animal detection system to serve as a baseline for our dataset. The Capsule Network is used to construct the aerial imaging system, while the rest of the systems use deep learning approaches such as fuzzy logic, fuzzy soft sets, and probabilistic neural networks.

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