LITERATURE SURVEY

Species determination using AI machine-learning algorithms: Hebeloma as a case study:

Peter Bartlett1et al (2022) proposed the work related to the species determination using AI and machine learning algorithms. They used the Hebeloma species as a case study and found that any species with sufficient datasets will find the best algorithm for processing it. The species identifier was able to identify 77% correctly with its highest probabilistic match, 96% within its three most likely determinations and over 99% of collections within its five most likely determinations.

METHODOLOGY:

For each tested group of characters, two identifiers were created–one that is trained on species and thus assigns a collection to a species, and one that is trained only on the (sub)section to which a training set collection belongs and thus assigns to a (sub)section too. The base software used was Python 3.7.8 , primarily developed and run on a Windows 10 laptop with typical hardware specifications but also tested on Linux. The scripts we developed were dependent on the following open source Python packages: PyTorch version 1.9.1, scipy v1.5.2 , pandas v0.25.1, numpy v1.19.2, dill v0.3.2 and reverse_geocoder v1.5.1 but did not depend on these specific versions in a critical way; other versions may be substituted. Interaction with the tool for both creating and verifying identifiers is carried out via a command line interface. Each functional form NN is implemented as a PyTorch torch.nn.Module instance with either one or two hidden layers. Each hidden layer has an activation function of either Rectified Linear Unit (ReLU) or Mish. The dimensionality of each hidden layer was set equal to the maximum of the dimensionality of the feature set and the dimensionality of the class.A total of five optimizers were used to minimise the loss function. For both the Adam and AdamW optimizers, the “AMSGrad” variation proposed was also evaluated.

ADVANTAGES:

This technique not only achieves good accuracy in identifying the species of a given collection but also has huge advantages over traditional single-access keys and multi-access keys. In addition to being able to seek out an optimal mapping between characters and species, it is also able to automatically learn and adapt to changes, such as the introduction of new species or even changes in species boundaries as more collections of a species become available and the definition widens

DISADVANTAGES:

Only one species was taken as a case study and the results were declared. It is not known whether it will work for all the species.

SOFTWARES DETAILS:

- Python 3.7.8
- PyTorch
- numpy v1.19.2
- scipy v1.5.2
- pandas v0.25.1
- dill v0.3.2
- reverse_geocoder v1.5.1.

Flukebook: an open-source AI platform for cetacean photo identification

Blount D et al (2022) proposed a work related to the open source AI platform called Flukebook. They determined which species are at greatest risk, where they are most vulnerable, and what the trajectories of their communities and populations are critical for conservation and management. Flukebook.org is an open-source web platform that addresses these gaps by providing researchers with the latest computational tools. It integrates photo-identification algorithms with data management, sharing, and privacy infrastructure for whale and dolphin research, enabling the global collaborative study of these global species. With seven automatic identification algorithms trained for 15 different species, resulting in 37 species-specific identification pipelines, Flukebook is an extensible foundation that continually incorporates emerging AI techniques and applies them to cetacean photo identification through continued collaboration between computer vision researchers, software engineers, and biologists. With over 2.0 million photos of over 52,000 identified individual animals submitted by over 250 researchers, the platform enables a comprehensive understanding of cetacean populations, fostering international and cross-institutional collaboration while respecting data ownership and privacy.

METHODOLOGY:

Flukebook is a web-based application. This breaks with a common paradigm of desktop-based photo ID tools for cetaceans, A web-based application allows users to access powerful machine learning algorithms running on high-powered servers without the need for any specialised equipment on their local machine. The site can be used from a web browser anywhere in the world with an internet connection reliable enough to upload and download images. Because it is a shared platform on a single server, it provides researchers with the ability not only to match photos within their own catalogue, but to compare with other data collectors who might have seen the same individuals.

ADVANTAGES:

The platform is free for approved users, and the Wild Me non profit organisation which develops and manages Flukebook has no plans to charge for its use at any point in the future.The main objects have unique web endpoints, such that any Encounter, Marked Individual, and Sighting has a static URL that can be referenced and linked, where all data fields can be inspected and edited by approved users.

DISADVANTAGES:

Globally distributed, wide-ranging whales and dolphins present a particular challenge in data collection because no single research team can record data over biologically meaningful areas. Hence, the cetacean and other ocean species data were insufficient and hence the result may be of less accuracy.

SOFTWARE DETAILS:

- SQL Databases
- Wildbook image analysis (WBIA)
- EXIF metadata
- Kaggle
- Computer Vision

Protecting endangered megafauna through AI analysis of drone images in a low-connectivity setting: a case study from Namibia

Hua A et al (2022) developed a method for protecting endangered megafauna through AI analysis of drone images in a low-connectivity setting by doing a case study from Namibia. Assessing the numbers and distribution of at-risk megafauna such as the black rhino (Diceros bicornis) is key to effective conservation, yet such data are difficult to obtain. Drones can deliver the required resolution and speed of monitoring, but challenges remain in delivering automated monitoring systems where internet connectivity is unreliable or absent. They described a model built to run on a drone to identify live images of megafauna. The model was less successful at identifying the other smaller objects which were not our primary targets: 0.34, 0.25, and 0.42 for ostrich (Struthio camelus australis), springbok (Antidorcas marsupialis) and human respectively. They used several techniques to optimise performance and overcome the inherent challenge of small objects (animals) in the data.

METHODOLOGY:

They gathered images and 4k videos of rhino and other megafauna from two different drones. They have also collected additional rhino drone footage in person and breaked the video into a dataset. To increase the size of the training dataset, they created additional synthetic images using two methods, a type of Generative Adversarial Network (GAN) and Adobe Photoshop. By using online data augmentation, they were able to increase the number and variety of training images that the model was exposed to without having to do additional labelling or manual manipulation. This helped the model generalise better to unseen data and avoid overfitting.

ADVANTAGES:

Faster R-CNNs are currently one of the most widely used architectures for these two stage detectors. One-stage detectors put the entire image through a single network and predict bounding boxes and object classes at the same time. They utilized YOLO as their real-time object detection model of choice because it has the fastest inference speed, which is essential for real-time video inference on a relatively low powered edge device.

DISADVANTAGES:

There is ongoing debate about the appropriate altitude AGL to fly drones for conservation. Any disturbance to animals will depend on several factors including species sensitivity, the noise generated by the specific aircraft, wind and air pressure variables, direction of approach, etc. Flying lower will result in higher quality images and greater detection rates with the drawback that it potentially disturbs the animals and has less ground coverage per flight. Flying higher will cover more ground and is less disruptive to the animals but the footage captured results in the animals being small objects, making accurate detection more challenging.

SOFTWARE DETAILS:

- CNN
- YOLO
- Adobe Photoshop
- Jetson NX
- MQ Telemetry Transport

Machine learning for image based species identification:

Jana Waldchen and Patrick Mader(2018) have proposed that work related to species identification as an essential component of workflows in biological research.This increase in biological image data in combination with modern machine learning methods,creates opportunities for automated species identification. Machine learning frameworks applicable to the species identification problem in today's world. Many activities, such as studying the biodiversity richness of a region, monitoring populations of endangered species,determining the impact of climate change on species distribution and weed control actions depend on accurate identification skills, this is done by using machine learning.These activities are a necessity for farmers, foresters, and naturalists.

METHODOLOGY:

The output of feature extraction is typically a vector which is then mapped to a score of confidence using a classifier. Depending on the application, the score is either compared to a threshold solely deciding whether an object is present or not (e.g. presence of a plant or animal in the image), or it is compared to other scores to distinguish object classes (e.g. species name). Prominent classification methods are machine learning algorithms such as support vector machines, Random Forest and artificial neuronal network (ANN).

ADVANTAGES:

Portable devices such as digital cameras and smartphones resulted in a large number of digital images that are openly available in online databases.Machine learning is user-friendly enabling people without substantial computer science background to individually apply the latest algorithms to their problems and datasets.

DISADVANTAGES:

The disadvantage is that applying the latest machine learning algorithms has initially slowed down their application in ecology and taxonomy research. When we compare studies that apply the same model architecture to a similar problem, they may report significantly differing results. Machine learning and multimedia information retrieval makes the proposed methods difficult to access for biologists.

SOFTWARE DETAILS:

- C++
- Python
- Julia
- Matlab
- Javascript
- Go
- R
- Scala
- Perl

Comparison of Deep Learning Techniques for Classification of the Insects in Order Level With Mobile Software Application

Michelle cristine and medeirous jacob (2022) has proposed the work related to Insects that are in a class of the arthropod branch and the most crowded animal group in terms of species and taxonomy. We produced a mobile-based decision support software with a deep learning model to classify and detect insects at the order level.we believe that this research will be beneficial to entomologists, naturalists, and other researchers in related fields.

METHODOLOGY:

The OpenCV library was integrated with Tensorflow and used in image processing with Python programming language commands. Python is an object oriented, interpreted, high-level programming language with its dynamic schema and modular structure that supports all kinds of data entry and class structures. Because it is platform-independent, it can be used in Unix, Linux, Mac, Windows, Amiga, Symbian operating systems. Also, the most crucial advantage that distinguishes Python from other programming languages is that it supports web applications, user interface applications, mobile applications, system applications, and databases. Python programming language was used in this study because the artificial intelligence and deep learning libraries are vibrant and easily adaptable.

ADVANTAGES:

The easy use of the model and mobile software proposed in this study, people who are not directly related to entomology but work in fields such as agriculture will detect insects that may damage agricultural products using the mobile app. We saw that the studies were generally carried out on insect species that are easy to distinguish and only for classification at the team level.

DISADVANTAGES:

The insect that is being too small in the image, the insect's image not being clear, and a different object in the image that makes it difficult to detect an object.

SOFTWARE DETAILS:

- Python
- C/C++
- Java
- Go
- R
- Matlab

Improving biodiversity protection through artificial intelligence:

Daniele Silvestro et al (2022) proposed a work on improving biodiversity protection through artificial intelligence and machine learning algorithms. They have tackled the challenge of optimising biodiversity protection in a complex and rapidly evolving world by harnessing the power of artificial intelligence. They designed a RL algorithm to find an optimal balance between data generation and the outcome.

METHODOLOGY:

They collect the data of and compare with the mazran model. Additionally, Marxan is typically used to optimise the placement of protected units in a single step. They tested a protection policy in which all protection units are established in one step. And they trained an additional model in CAPTAIN based on a full initial monitoring. The CAPTAIN outperforms Marxan in 64% of the cases with an average improvement in terms of prevented species loss of 9.2%.

ADVANTAGES:

This technique achieves a good accuracy. It succeeds in protecting on average 26% more species than a random protection policy. They have achieved a 22% of each species range found within protected units, well above the set target of 10% .

DISADVANTAGES:

Data monitoring and storing is the slight disadvantage in this case study.

SOFTWARE DETAILS:

- Python
- Numpy
- Pandas
- RL framework

AI Naturalists Might Hold the Key to Unlocking Biodiversity Data in Social Media Imagery:

Tom A. August et al(2020) proposed a work related to unlocking biodiversity data using social media networks. They found over 60,000 geolocated images tagged with the keyword "flower" across an urban and rural location in the UK and classified these using AI, reviewing these identifications and assessing the representativeness of images. Images were predominantly biodiversity focused, showing single species. Non-native garden plants dominated, particularly in the urban setting. The AI classifier performed best when photos were focused on single native species in wild situations but also performed well at higher taxonomic levels (genus and family), even when images substantially deviated from this. They presented a checklist of questions that should be considered when undertaking a similar analysis. AI can also be used to extract information from big data in order to address various challenges faced by society.

METHODOLOGY:

Flickr is a website used for image hosting and has an application programming interface (API) that allows queries of the image database. Flickr images were classified using a deep learning-based classifier trained on Pl@ntNet data. Pl@ntNet is a participatory research and educational platform for the production, aggregation, and dissemination of botanical observations.47,48 Initiated in 2009, it relies on a web and mobile infrastructure to support the identification of plants by AI classification. It covers a significant part of the European and North American flora, and an increasing number of species in tropical regions. Images are classified by a CNN that is periodically trained in a supervised manner on the valid plant observations produced and revised by the Pl@ntNet user community. Flickr images were submitted one-by-one to the API, and only the taxonomic identification associated with the highest classification score was retained for each image. No thresholding on the classification score was applied. Only the classification scores and image metadata were stored, Flickr images were not downloaded.

ADVANTAGES:

Most of the reviewed images were of horticultural plants and a significant proportion were introduced by humans to their photographed location, whether in- or outdoors. This varied significantly between landscape settings, with shots of horticultural species, indoor plants, and introduced occurrences generally being lower in the rural setting of the Peak District than in the urban setting of London. This division was also clear in terms of the national native or non-native status of species. Flickr was used because of its accessibility and rich metadata, which allowed us to filter images using text and spatial searches.

DISADVANTAGES:

Image licences are of critical interest for such research. In this case, as the main objective was to evaluate plant biodiversity, the AI classifier has to deal with a much larger number of visual classes (i.e., species). This increases the difficulty, but recent progress in automated plant species identification reinforces the belief that this type of study will become easier in the years to come.

SOFTWARE DETAILS:

- Flickr
- Pl@ntNet
- CNN algorithms
- Google StreetView

Insect detection using a machine learning model:

Somjit Homchan and Yash Munnala Gupta(2021) proposed work related to the Insect detection using Machine Learning model. Here they used House Cricket species as a case study. They aim to classify insect and their sex by supervised machine learning (ML) model. They develop ML models for Acheta domesticus and Gryllus bimaculatus species classification and sexing. An experimental investigation was conducted to detect using pre-processed 2646 still images. Out of the 2646 images, 2247 were used for training ML models and 399 were used for testing the trained model. The prediction accuracy of trained model had 100 % accuracy to identify both species and their sex.

METHODOLOGY:

For the Image pre-processing, specimens were placed on white paper and 4K video at 30 frames per second (fps) was taken from all directions. Recorded 4K videos were used to extract frames for machine learning using Google Teachable Machine (GTM). GTM uses TensorFlow.js (Javascript library for machine learning). Extracted JPEG images were rectangular with the resolution of 500 dots per inch (DPI) having the dimension of 1280 X 720, JPEG images were separated into four different folders before uploading them into four classes on GTM server. To evaluate the model, the advanced parameters were used at GTM platform to compute accuracy per cricket species class, accuracy per repetition, loss per repetition, and to generate confusion matrix.

ADVANTAGES:

This study is the first step towards educating researchers, to use machine learning from the GTM platform in biological sciences. And this model has an accuracy of nearly 98% - 100%. The developed algorithm can be used via an online platform, or can be used with a mobile application ,developed to run ML models in the real environment.

DISADVANTAGES:

They had studied only two species in House Cricket. The accuracy becomes less if other species in the same family have similar characteristics.

SOFTWARE DETAILS:

- Google teachable machine (GTM)
- Python 3.7.8
- TensorFlow library

SUMMARY:

The above proposed methods have solved many major problems in the species identification in a specific different manner. The images were taken for processing form photographs, drone images and even social media. The images were processed using CNN algorithm and many different processing methods. However, they all take a specific species as a case study to work on their algorithm or take either flora and fauna as their work. Hence a single web application which identifies the species more accurately is needed.

PROPOSED WORK:

- The proposed work contains a web application in which when an image is given, it could identify the species and classes name with the help of a deep learning model.

- The CNN algorithms are to be used for image processing and image segmentation where the train sets are fed into the CNN algorithm to get the output accurately.

- It will help the naturalists to identify the birds, flowers, mammals and other species they see on their hikes, canoe trips and other excursions.

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