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Identification and Recognition of Diverse Species Using Deep Learning

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Abstract

This paper presents a method for neural network-based identification and recognition of an extensive variety of flora and fauna. The system that has been proposed was designed to assist field naturalists, people who take special attention to and identify patterns that exist in the wild identify various species. Utilizes a Digital Naturalist dataset, which was created by gathering photos from numerous internet sources and camera-captured images. Our solution revolves around a Convolutional Neural Network (CNN) which employs a deep learning model built on the InceptionV3 architecture. The model is trained using a large set of photos from several subclasses, such as birds, flowers, and animals. Using the Flask framework, the trained model provides the basis for the creation of a simple web application. This application makes predictions in real time based on input photographs, making species detection more convenient for field naturalists. The web application enhances the accuracy and thoroughness of information by directing users to the relevant Wikipedia page, once they submit an image and click the "predict" button. This holistic strategy creates a greater interest in conservation by enabling researchers, field naturalists, and visitors to communicate with the natural world in an effortless way.

Keywords:

Flora and Fauna, Species Identification, Deep Learning, InceptionV3, CNN, Classification, Flask Web Application.

1. INTRODUCTION

Artificial intelligence has advanced significantly in the last few decades, and pattern recognition is now an essential part of many practical applications. Naturalists are among those who have made significant contributions to this field. They are those who closely examine and identify the various patterns that may be discovered in nature. This paper explores the difficulties encountered by naturalists, especially by zoologists who study fauna, botanists who study flora, and general naturalists who study living forms. Due to the enormous and unknown diversity of species, these professionals struggle with classification, research, identification, and eradication concerns, which makes it difficult for them to digest information quickly and effectively wherever they may be.

Identification of plants and animals is a complex process that is very important to the general public as well as practitioners. Field naturalists work together to understand and protect biodiversity by carefully cataloguing and comprehending the wide variety of species they come across in their explorations. The incorporation of deep learning models offers a previously unheard-of chance to improve and accelerate the identification process in the age of technological developments.

Going on an outdoor adventure typically means using conventional methods, such bringing along a guidebook or asking seasoned ornithologists for advice. This study proposes a deep learning and neural network-powered web application as a solution. The intention is to provide field naturalists with a useful tool for recording, identifying, and showcasing the beauty of the natural world at any time and from any location.

Field naturalists play an even more important role since the loss of biological diversity due to species extinction demands a deep grasp of species. We propose developing a web application to help naturalists recognize birds, flowers, mammals, and other species they come across on their travels in order to meet this demand. The core of the application is a deep learning model that has been trained on a variety of datasets including various species, producing a flexible instrument for species identification.

Naturalism is characterized by diversity, which reflects a broad range of perspectives on philosophy and science. Naturalists have one thing in common: they are proud of science and what it has accomplished. In order to develop a user-friendly platform that meets the many interests and backgrounds of field naturalists, this initiative recognizes and celebrates this variety. Our application primary benefit is in its use of deep learning methods to integrate three distinct species into a single web interface. Notably, this technique can be applied to inexpensive devices like cameras and does not require specialized hardware, making it accessible to a wide range of users. This application aims to support conservation efforts spearheaded by groups such as the NCC by bridging the gap between technology and fieldwork conducted by naturalists.

To sum up, it aims to investigate the relationship between deep learning, biodiversity, and the real-world requirements of field naturalists. With the launch of an intuitive web application, our goal is to enable naturalists to quickly and correctly identify the species they come across, encouraging a closer relationship with the natural world and the exchange of important knowledge for conservation.

2. PURPOSE OF THE PAPER

Our paper serves a dual purpose: it advances the field of artificial intelligence while supporting field naturalists. First, we examine the difficulties presented by the huge and unidentified diversity of species that naturalists have come across in their travels. We present an innovative method—augmenting the dataset—to overcome the drawbacks of small datasets. Our goal is to improve the performance of machine learning models, namely the Convolutional Neural Network (CNN) method that we are using in this research, by virtually growing its size. This augmentation procedure adds to our deep learning model's general resilience while also expanding the range of species representation.

Our paper's second key component is the pre-processing of photographs to convert them into a machine-readable format. This crucial stage guarantees that the features and patterns in the photos can be efficiently extracted by our deep learning algorithm, enabling precise species identification. We clarify the importance of this pre-processing phase and highlight how it gets the data ready for the CNN algorithm to be used later.

The third aspect of our project is a thorough investigation of how the CNN algorithm operates on the enhanced and pre-processed dataset. Our goal is to disentangle deep neural networks and comprehend how they make predictions about the class and subclass of an image. We explore the underlying workings of the model, elucidating the several levels of abstraction that support its predictive power. Furthermore, we evaluate the model's accuracy and offer insights into how well it performs in categorizing different species.

Finally, our paper goes beyond the domain of developing and analyzing models to the real-world implementation of our discoveries. With the goal of creating a user-friendly tool that enables field naturalists to effortlessly capture, identify, and share the beauty of the natural world, we set out to construct web applications using the Flask framework. Our efforts have culminated in this fusion of technology and usefulness, which builds a bridge between the practical demands of individuals committed to studying and protecting biodiversity and the capabilities of artificial intelligence.

3. LITERATURE SURVEY

The study offers [1] two detection techniques together with a unique dataset of wild ungulates that were gathered in Latvia. Object localization, categorization, and picture embedding are all included in the detector structure. Deep neural networks (DNNs) use convolutional layers to extract features, and they frequently use pre-trained backbone networks like ResNet50 and other networks from Image Net. In order to take advantage of data pattern distribution across many feature map scales, a Feature Pyramid Network (FPN) processes inputs from numerous backbone layers. A feed-forward neural network handles the classification or regression task.

Using an alternate approach, the research Work focuses on creating a YOLOV3 model [2] for darknet algorithm-based animal identification. The model divides incoming photos into various widths and lengths using a pre-trained coco dataset for detection. The recognizer deep learning package is used by the YOLOV3 model to recognize images and show the name of the recognized animal. A variety of training and testing photos from the dataset are used to evaluate performance.

Another work aims to identify bird species using Inception-ResNet-v2 and a transfer learning-based approach. In order to increase reliability, the model is trained to identify and categorize different species of birds [3] using a method that involves switching incorrectly categorized data between training and validation datasets. Retraining using swapped data is part of the process that continues until ideal outcomes are attained. Fivefold cross-validation is also carried out to evaluate the model's predictive ability.

An alternative method concentrates on classifying and identifying plants [4] using a leaf analysis method. In this method, plant leaf images are segmented, and then an advanced feature extraction algorithm is used to extract important aspects including leaf shape and texture. The suggested artificial neural network is then used to recognise different plant species by applying the back propagation error method (BP algorithm). This method makes use of image analysis tools to identify and categorise different plant species according to the characteristics of their leaves.

In this method [5] the technology collects morphological characteristics from plant leaves, emphasising the importance of leaf shape as a critical component for plant identification. In order to improve accuracy, a Multilayer Perceptron and additional classification methods, such as the AdaBoost approach, are used in the classification process. Various classifiers, including KNN, Decision Tree, and Multilayer Perceptron, are used to assess how well the algorithm performs in precisely identifying different plant species. The Automatic classification of animal images remains an unsolved problem due to the challenges in images. When it comes to image classification and recognition, animals are the difficult ones [6].

Many people visit bird sanctuaries to observe the various bird species or to admire their elegant and beautiful feathers, often without recognizing the differences between the species and their unique features. Understanding these differences can enhance our knowledge of exotic birds, their ecosystems, and their role in biodiversity [7]. The extent to which these models can be generalized is not well discussed. Many models are created for certain domains, such ungulates in the wild, birds, or plants, which raises questions about how well-suited they are to a variety of unusual and diverse situations.

The effectiveness of machine learning algorithms largely relies on the quality of the input data representation. If the features are not properly constructed from the raw data, the algorithms may fail to correctly distinguish between different data classes [8]. One significant disadvantage is the lack of evidence regarding the performance of these models on larger datasets or in real-world scenarios.

Although some models use data swapping and transfer learning to improve generalization, there isn't much discussion of how well these strategies work to avoid overfitting. Improper management of overfitting may result in models that function well on training data but poorly on novel, unseen cases. Decades of research have informed hundreds of scientific articles on the effects of production forest management on wildlife, including birds, but there has been little consensus on their applications or broad considerations to inform conservation [9]. As illustrated in Table 1, recent techniques and approaches in species identification are summarized.

Table 1. Overview of Recent Techniques and Approaches in Species Identification

Techniques/ Approach	Authors	Year	Description
Object Localization and Categorization	Daniel L. Silva, Manuel J. S. Silva, Bruno G. Fernandes, Eduardo M. M. Silva	2021	Uses convolutional layers in DNNs with pre-trained backbones like ResNet50 and FPNs for multi-scale feature extraction.
Leaf Analysis	K. Zhang, Y. Zhang, M. Liu, J. Wang	2021	Focuses on plant classification through leaf analysis using segmentation and feature extraction. Employs various classifiers, including Multilayer Perceptron, KNN, and Decision Trees.
Morphological Features	A. V. Patel, S. K. Sharma, N. P. Rathi	2022	Focuses on plant species classification using morphological features of leaves. Employs various machine learning techniques, including Multilayer Perceptron, KNN, and Decision Trees.
YOLOV3	G. Chen, Q. Liu, S. Wang, Y. Zhang	2023	Employs the darknet algorithm with a pre-trained COCO dataset for object detection and classification through a deep learning package.
Bird Species Identification	Martynas Jurkonis, Tomas Šuminas, Romas Šuminas	2024	Utilizes ResNet50 with transfer learning and data augmentation to enhance bird species classification. Employs techniques to address misclassification through data swapping and fivefold cross-validation.

In our proposed work, we employ InceptionV3 with transfer learning to enhance its applicability across various contexts. The focus is on ensuring robust generalization and conducting comprehensive evaluations to enable flexible and scalable species identification. In summary, the model exhibits improved generalization skills by utilizing the InceptionV3 architecture and applying transfer learning, which positions it for a variety of species identification tasks. In contrast to many assessed models that are customized for particular domains, the suggested approach demonstrates a wider range of application, guaranteeing its efficacy in a variety of species and environmental settings. The suggested model's legitimacy and dependability are further increased by the focus on thorough evaluations and the application of standardized criteria. Essentially, our work closes current gaps and lays the groundwork for future deep learning species identification systems that are more flexible and scalable.

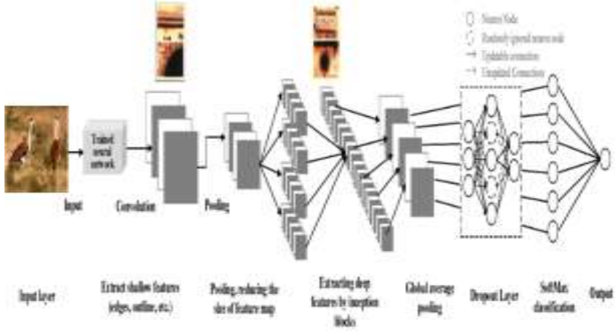

Figure 1. InceptionV3 Architecture

As depicted in Figure 1, the Inception V3 architecture is detailed. The core of the architecture is made up of Inception modules, which perform parallel convolutions with different filter sizes (1x1, 3x3, 5x5). This allows the network to capture information at different scales. The output of these convolutions is concatenated to form the final output of the module. The inception modules also include 1x1 convolutions as dimensionality reduction steps before applying more computationally expensive convolutions like 3x3 and 5x5. This reduces the number of parameters and improves computational efficiency.

To further improve efficiency, larger convolutions (e.g., 5x5) are factorized into smaller convolutions (e.g., two 3x3 convolutions). This reduces computational cost while preserving the receptive field. The network includes auxiliary classifiers, which are intermediate classifiers placed after some layers in the network. These classifiers provide additional gradient signals during training and help prevent the vanishing gradient problem in deeper networks. The auxiliary classifiers are typically discarded during inference, but they are useful during training to regularize the network and improve convergence.

4. PROPOSED METHODOLOGY

The step-by-step process used in the system's development and implementation is described in the suggested methodology. The procedures for gathering data, preparing it, training models, and integrating AI algorithms are all covered in detail in this section. The architecture, workflow for identification of species are detailed.

4.1 Data Collection

Training machine learning models need datasets, which are essential. A variety of datasets were gathered for this study in order to guarantee the correctness and robustness of the model. One of the steps in the data collection procedure was taking pictures with a camera.

Database Schema: Three primary categories, or datasets, comprise the gathered data, each of which represents a different class of objects or entities. The datasets include Mammal, Flower, and Bird.

a) Bird collection: This collection includes pictures of different kinds of birds. Two particular classes were taken into consideration:

1. Great Indian Bustard Bird: Photographs that highlight this bird's unique characteristics.
2. Spoon Billed Sandpiper Bird: Pictures that highlight the distinctive qualities of this species of bird.

b) Flower Dataset: Photographs of several flower varieties make up the Flower dataset. There were two designated classes:

1. Corpse Flower: Pictures showing off the Corpse Flower.
2. Lady Slipper Orchid Flower: Photographs showcasing the Lady Slipper Orchid Flower.

c) Mammal Dataset: Photographs of several mammalian species are included in the Mammal dataset. There were two distinct classes identified:

1. Pangolin Mammal: Pictures of the Pangolin Mammal.
2. Seneca White Deer Mammal Images: This section features images of the Seneca White Deer Mammal.

Figure 2 presents the block diagram of the proposed model.

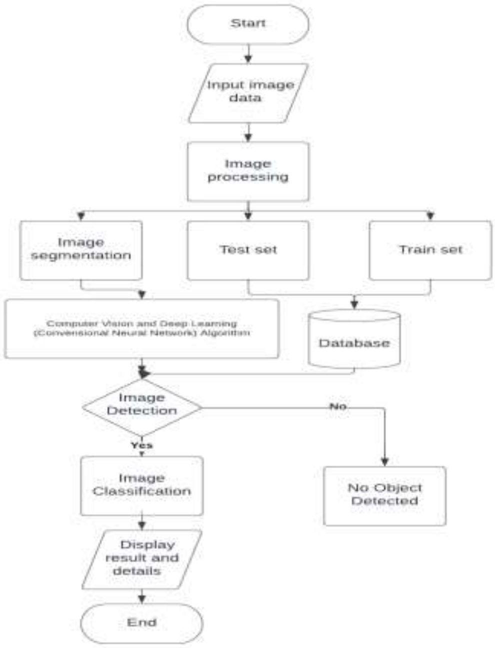

Figure 2. Block Diagram of Proposed Model

4.2 Data Preprocessing

Building a strong and functional deep learning model requires completing the data preprocessing stage. In order to train a neural network, raw data must be prepared and transformed into an appropriate format. This section describes the procedures used to prepare the Digital Naturalist Dataset for a species categorization model. To improve model performance, the dataset is split into training and testing sets. Various strategies have been applied to each class to improve the model's performance.

4.2.1 Data Augmentation

Data augmentation is a method used to add different alterations to the pre-existing images in order to artificially improve the diversity of the training dataset. This enhances the model's performance on untested data and helps it generalize more effectively. In this paper, the augmentation procedure consists of

- Up to 30 degrees of rotation
- Change in width of up to 10%
- Change in height of up to 15%
- Up to 25% shear transformation
- Enlarging by up to 20%
- Flipping horizontally - Changing brightness between 0.5 and 1.2

The Keras Image Data Generator is used to execute the augmentation, producing an augmented dataset produced for each original image.

4.2.2 Species Image Sizes

The dataset's species photos have been scaled to 224 by 224 pixels, which is the industry standard. In order to guarantee compatibility and effective training, this is a standard procedure when working with pre-trained CNN models, such as InceptionV3.

4.3 Building and Training the Model

This section explains how to use the Digital Naturalist dataset to design and train a deep learning model for image categorization. We pre-trained the InceptionV3 architecture and adjusted it to our particular categorization objective. Images of several categories, including birds, flowers, and mammals, are included in the dataset.

4.3.1 Model Building

Because the InceptionV3 architecture has shown to be successful in image recognition tasks, we decided to use it as the foundational model. Since we planned to modify the output layer for our particular classification task, the top layer of this model was loaded without it.

4.3.2 Freezing Pre-trained Weights

We froze the weights of the InceptionV3 model in order to take advantage of its pre-trained features. This way, only the weights of the newly added dense layer would change during training. When utilizing transfer learning, this phase is essential to preserving the important information stored in the pre-trained weights. Let $f(x;\theta pre)$ represent the output of the pre-trained model (InceptionV3 in this case) with input x and pre-trained weights θpre .

4.3.3 Customizing the Model

The output of the InceptionV3 basic model was supplemented with a dense layer with a sigmoid activation function after a layer was flattened. Since our objective involves multi-label classification—in which an image can belong to more than one class—we opted for a sigmoid activation.

4.3.4 Model Compilation

The binary cross entropy loss and Adam optimizer were used to assemble the model, making it appropriate for multi-label classification. We decided on accuracy as the key performance indicator to track the model's development during training. Let g(f(x;θpre);θnew) represent the output of the newly added dense layer with parameters θnew .

4.3.5 Data Augmentation

In order to improve the generalization capability of the model, we implemented data augmentation methods. The dataset's photos underwent arbitrary horizontal flips, rotations, shifts, shearing, and zooms. We also changed the brightness levels, which resulted in differences in the dataset. For subsequent usage, these enhanced photos were kept in a different directory.

4.3.6 Loading and Preparing the Dataset

The Image Data Generator class from Keras was utilized to load the datasets for training and testing. To match the input size required by the InceptionV3 model, the photos were scaled to 224x224 pixels. A mapping between class labels and numerical indices was made possible by the identification of the class indices.

4.3.7 Model Checkpoint and Early Stopping

To preserve the model with the highest accuracy during training, we used Model Checkpoint. Early Stopping was used to stop training if the accuracy increase of the model was less than a predetermined threshold.

4.3.8 Model Training

The fit function was used to train the model during a 30-epoch period. The model's performance was tracked during training, and appropriate checkpoints were saved. Iterating through batches of photos from the training dataset, updating the model weights, and testing on the validation dataset were all part of the process.

4.3.9 Exporting the Model

The model architecture and weights were saved to files (DigitalNaturalist.h5 and Digital Naturalist.json) and Digital Naturalist, respectively, following a successful training session. This phase makes sure that future reconstruction and prediction using of the trained model is possible without the need for retraining. The following hyper parameter choices are used in the work, as shown in Table 2.

Table 2. Parameter values used

Parameter	Chosen Value
Learning Rate	0.001
Batch Size	128
Number of Epochs	10
Dropout Rate	0.3

4.4 Integration of AI Algorithms with Flask

The integration of deep learning techniques, a type of artificial intelligence (AI), with a Flask web application for species detection and classification is demonstrated in this section. Using data augmentation techniques, the AI model is trained using a dataset of photos of different species, such as flowers, mammals, and birds, in order to improve its resilience. Users can input photos for real-time species prediction by integrating the learned model into a Flask web application.

4.4.1 Integration of Flask

In order to save weights for the model parameters and to reflect the architecture, the trained model is exported to a JSON file. Images supplied by users are intended to be used in the Flask web application for species prediction. Using the InceptionV3 model, the application predicts the species from the provided photographs and provides a link to further information on the species**.**

4.5 Features of Web Applications

The home page and the prediction page are the two primary paths through the Flask web application. On the prediction page, users can upload photographs, and the application offers real-time feedback on the species predictions. For monitoring purposes, the forecasts are recorded in the server console. Figure 3 illustrates the solution architecture.

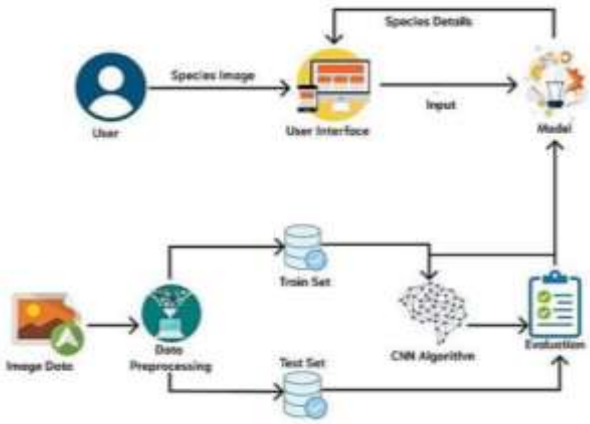

Figure 3. Solution Architecture

4.6 Accessibility and Web Interface

The incorporation of artificial intelligence algorithms into Flask offers an intuitive interface for the identification and categorization of species. With the help of the suggested method, users can communicate with an advanced deep learning model without needing to understand the underlying code. It is possible to expand this integration across other domains, which will aid in the creation of AI applications that are easily accessible and user-friendly.

1. Gather a varied collection of photos showing numerous creatures including mammals, flowers, and birds.
2. Use methods like rotation, shifting, shearing, zooming, and flipping to improve the dataset. This method is called "data augmentation."
3. Make use of the InceptionV3 pre-trained deep learning model to extract features and patterns from the annotated dataset. In order to preserve important information, train the model to correctly classify photos into distinct species categories by freezing the acquired features.
4. Create a web application with the approachable Python web framework Flask. Users will be able to interact with the trained AI model using this application.
5. Permit users to submit photos of the species they wish to identify. In this phase, they will choose an image from their device and upload it via the web application.

6. Analyze the uploaded image and identify the species using the trained InceptionV3 model. Using the trained dataset as a basis, the model makes precise predictions by utilizing its learned features.
7. Provide links to the Wikipedia articles related to the anticipated species. This makes it possible for users to obtain thorough information about the recognized species rapidly.

5 RESULTS AND DISCUSSIONS

Inception V3 remains a strong contender for species recognition, with high accuracy, F1 score, and recall. However, ResNet-50 and Efficient Net may offer slight improvements in certain scenarios, especially with optimized datasets or where computational efficiency is a priority. VGG16 and MobileNetV2, while useful in specific contexts, generally lag behind in terms of accuracy and recall, particularly in complex species identification tasks. The choice of model should depend on the specific requirements of the task, including dataset size, species diversity, and computational resources available. The model parameters and comparisons with other models are summarized in Tables 3 and 4.

Table 3. Model Parameters

S.No	Parameter	Values
1.	Model Summary	Total params : 22,704,966 Trainable params : 22,704,966 Non-trainable params : 0
2.	Accuracy	Training Accuracy - 92.73% Validation Accuracy – 80.73%

Table 4. Comparison of models

Model	Accuracy	Recall	F1-score
Inception V3	92.73	0.91	0.90
ResNet-50	92.0	0.92	0.89
VGG16	88.5	0.85	0.84
Efficient Net	92.5	0.93	0.89
MobileNetV2	87.5	0.84	0.84

- Accuracy: The percentage of correctly classified species.
- F1 Score: The harmonic mean of precision and recall, reflecting the balance between them.
- Recall: The ability of the model to detect all true positive species examples.

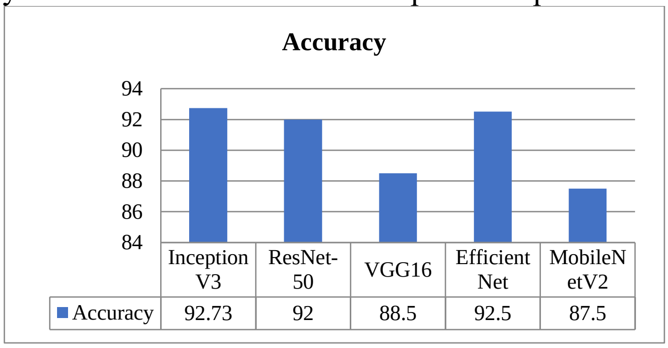

Figure 4. Showing accuracy of different models

Figure 4 shows a bar chart that visualizes the accuracy of different models. Figures 5 and 6 illustrates recall and F1-score, respectively.

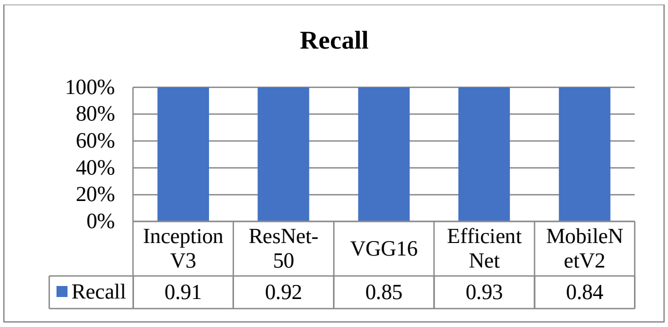

Figure 5. Showing Recall of different models

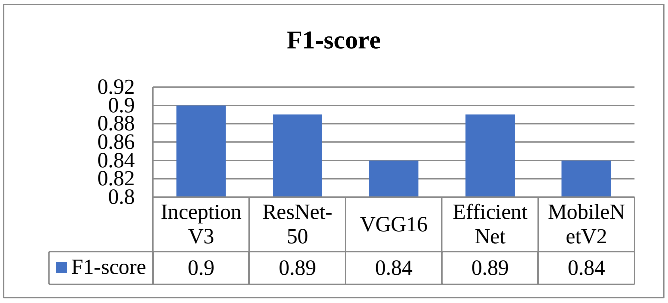

Figure 6. Showing F1-score of different models

We can determine the predictive accuracy of our model by evaluating each species with in its own subcategory.

6. CONCLUSIONS AND FUTURE WORK

In conclusion, this paper skillfully combines an intuitive online interface with artificial intelligence. When users upload photos of the species they wish to identify, the system recognizes it accurately because it was trained on a wide range of datasets. Instantaneous results are shown, along with links to additional Wikipedia pages. This approachable and ever-evolving system bridges the gap between cutting-edge technology and intuitive user interface by providing a straightforward but effective tool for species recognition. Eventually, the algorithm will be expanded to recognize species via audio recordings or ambient data in addition to photos.

Making a mobile application that operates in real-time is another exciting avenue. The development of an intuitive mobile interface would enable people to quickly identify species using their smartphones, encouraging citizen research and interaction with the environment.

Adding more language support to the web application would improve inclusivity and reach the project's target audience worldwide. The project's utility in a variety of contexts would also be increased by adding an offline mode to the smartphone application, which would allow users to identify species in places with spotty or nonexistent internet connectivity.

While the current system excels in image-based species recognition, future work could involve extending the algorithm to recognize species through audio recordings and ambient environmental data. This would enable the identification of species based on bird songs, insect noises, or other natural sounds, providing a richer and more versatile tool. Integrating NLP models to process user queries in various languages and dialects would enhance the system's usability. Machine translation services could be employed initially, but human translation would be ideal for accuracy and localization.

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