Malnad College of Engineering, Hassan

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A Mini Project Report

On

"Leafopedia:Leaf Recognition and Tree Information Retrieval using Deep Learning"

Submitted in partial fulfillment of
the requirements for the award of the degree of

Bachelor of Engineering
in
Computer Science and Engineering

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Certificate

This is to certify that mini project work entitled **"Leafopedia"** is a bonafide work carried out by **P G Prajwal (4MC20CS101) Ranjan H T (4MC20CS121) Sevantkumar S Huggi (4MC20CS137) and Shamanth R S (4MC20CS139)** in partial fulfillment for the award of Bachelor of Engineering in Computer Science and Engineering of the Visvesvaraya Technological University, Belgavi during the year 2022-2023. The project report has been approved as it satisfies the academic requirements in respect of mini project work prescribed for the Bachelor of Engineering Degree.

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ABSTRACT

Medicinal plants are gaining attention in the pharmaceutical industry due to having less harmful effects reactions and cheaper than modern medicine. Based on these facts, many researchers have shown considerable interest in the research of medicinal plants recognition. There are various opportunities for advancement in producing a robust classifier that has the ability to classify medicinal plants accurately in real-time. Various effective and reliable deep learning algorithms for plant classifications using leaf images that have been used in recent years are reviewed. The review includes the image processing methods used to detect leaf and extract important leaf features for some deep learning classifiers. These deep learning classifiers are categorised according to their performance when classifying leaf images based on typical plant features, namely shape, vein, texture and a combination of multiple features. The leaf databases that are publicly available for plants recognition are reviewed as well and we conclude with a discussion of prominent ongoing research and opportunities for enhancement in this area..

Committed to advancing botanical and medicinal research, our project employs deep learning algorithms for the accurate and rapid identification of plant species. This project utilizes the "Indian Medicinal Leaves Datasets". Beyond mere recognition, our system provides users with comprehensive insights into the medicinal properties associated with each identified plant species. This encompasses detailed information on the plant's therapeutic benefits, chemical constituents, traditional uses in medicine, and any relevant historical or cultural significance. The experimental results robustly affirm the efficacy of our proposed methodology in achieving not only precise species identification but also in furnishing a wealth of knowledge on the diverse medicinal attributes of plants. Our project serves as a pivotal contribution to the convergence of image processing and machine learning technologies, propelling advancements in both botanical science and medicinal research, and offering a promising avenue for further interdisciplinary exploration.

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TABLE OF CONTENTS

LIST OF FIGURES

Chapter 1

Introduction

1.1 Introduction to the project

In an era where urbanization and technological advancements have distanced humans from nature, the identification and utilization of medicinal plants have become increasingly challenging. Recognizing the importance of fostering a connection between individuals and their natural surroundings, our project endeavors to employ cutting-edge Machine Learning (ML) techniques to empower people with the ability to discern medicinal plants based on their leaves.

The primary motivation behind this initiative stems from the inherent difficulty humans face in distinguishing various plant species, particularly those with medicinal properties, within their immediate environment. With the rise of urban landscapes and diminishing knowledge of traditional plant uses, the invaluable wisdom embedded in nature is at risk of being lost. Our ML model seeks to bridge this knowledge gap by harnessing the power of computer vision to analyze leaf characteristics and accurately identify medicinal plants. This technological intervention aims to revive and enhance humanity's connection with the healing properties present in the plant kingdom.

In the present times, where health and well-being are paramount, the significance of our project is multifaceted. Firstly, it addresses the urgent need for people to reconnect with nature and tap into the vast repository of medicinal plants that surround them. By democratizing the ability to identify these plants through the use of ML, we empower individuals to explore natural remedies for common ailments and foster a deeper appreciation for the ecosystem.

In conclusion, our project represents a timely and crucial endeavor that aligns with the evolving needs of society. By leveraging ML to identify medicinal plants and tapping into the vast knowledge reservoir of ChatGPT, we aim to empower individuals to make informed choices about their health, fostering a harmonious coexistence between humanity and the natural world. This initiative not only addresses the current disconnect between people and nature but also promotes a sustainable and holistic approach to healthcare in the modern age.

1.2 About Project

1.2.1 Problem Statement

In a world where the appreciation of biodiversity and the environment is paramount, there exists a need for an innovative solution that seamlessly integrates modern technology with the natural world. The challenge lies in developing a comprehensive platform that harnesses the potential of advanced deep learning techniques. This platform must facilitate instant access to detailed information about diverse tree species using deep learning algorithms to accurately identify tree species from leaf images. This solution should not only enhance users' understanding of trees but also foster a deeper connection with nature, promoting education, engagement, and ecological awareness. Additionally, the challenge involves refining pre-processing methods to ensure the deep learning model's accuracy and robustness. The project aims to bridge the gap between technology and the environment, creating an interactive and educational experience that encourages users to explore, learn, and contribute to the world of trees.

1.2.2 Objective

The main objective of the project is to develop a method of identification of trees and display information about trees to the users through an elegant user interface. The below mentioned steps will be performed to achieve the stated objective.

- Utilize advanced deep learning techniques to create a robust model capable of identifying tree species accurately from leaf images.
- Create an engaging user experience deep learning, allowing users to identify trees in their surroundings through technology.
- Validate the model's performance with real-world leaf images to ensure its robustness.
- Iterate on deep learning model to ensure consistent accuracy and an evolving, user-centered experience.

1.3 Organization of Report

In chapter 1 introduction to the project, problem statement and objectives is being discussed. In chapter 2 literatuere survey on related project is being discussed. Chapter 3 discusses about dataset segmentation and Model Training, and Cloud Computing. Chapter 4 contains results of the project. Chapter 5 consists conclusion to the project.

Chapter 2

Literature Survey

- This chapter provides a concise overview of key research papers relevant to our project.
- This chapter delves into the key findings of specific research papers related to our project, outlining their core contributions and relevance to our goals.
- We navigate through relevant papers, extracting the critical insights that guid our project's direction

Anuradha et al. [1] presents an approach that attains optimal identification accuracy through the adept integration of geometry, color, and texture, employing sophisticated image processing techniques. By calculating features for diverse herbaceous leaf types, the study facilitates the storage of training outcomes within a comprehensive database. The results unveiled in the study emphasize the superiority of convolutional neural networks (CNNs) when compared to multi-layered perceptions in terms of validation and testing performance. Conclusively, the research findings highlight that a CNN model trained with RGB images showcases superior performance compared to the grayscale-trained CNN counterpart.

Chung et al. [2] introduces a pioneering concept of central attention, firmly grounded in user experience analysis and prior research. This novel approach enhances the emphasis on target elements while minimizing distractions from image backgrounds. This strategic adjustment plays a crucial role in mitigating confusion during model training for accurate tree species recognition. Subsequently, the study formulates a dual-path convolutional neural network (CNN) model. Within this architecture, distinct sub-networks operate autonomously, individually processing either the original images or centrally cropped versions. The resultant outputs from both sub-networks are harmoniously merged through a concatenation layer.

Aslan et al. [3] here convolutional neural networks (CNNs) using both machine learning (ML) and deep learning (DL) are used to classify leaves. Through preprocessing, grayscale pictures are produced, and SURF (Speeded Up Robust Features) are then extracted. Features are organised using Bag of Visual Words (BoVW), and histograms are produced. Decision Tree (DT), k-Nearest Neighbour (KNN), Naive Bayes (NB), and Support Vector Machine (SVM) are the four ML techniques used, and Bayesian optimisation is used to optimise the hyperparameters. The maximum accuracy, 98.09%, is achieved by KNN. In terms of accuracy, DL models such as ResNet18, ResNet50, MobileNet, GoogLeNet, and DenseNet beat ML techniques.

Pushpa et al. [4] proposed a productive approach for classifying Ayurvedic plants using machine learning and digital image processing. Pre-processing, feature extraction, and classification make up its three stages. The method entails computing the leaf factor using the retrieved characteristics and contrasting it with values from a trained database. The suggested technique successfully classifies Ayurvedic plant species with an accuracy of 93.75

Zhang et al. [5] presented the GLMMDP method for recognising plants, which is based on MNMDP. Incorporating both local and class data, GLMMDP also takes into account neighbourhood dispersion within and across classes. For the construction of the projection matrix, it minimises local intra-class scatter while maximising local inter-class and global between-class scatters. On ICL datasets, GLMMDP achieves over 95% accuracy, while on Leafsnap datasets, it achieves over 90% accuracy.

Zhang et al. [6] used DPCNN and BOF and combined BOF_SC and

BOF_DP, presented new leaf image characteristics. SVM is ues as classifier, these traits are used in plant recognition. Tested the technique using four well-known leaf datasets and compared BOF_DP to already-existing features on the Flavia dataset. On typical leaf datasets, the method—which included both characteristics with a linear SVM classifier—achieved more accuracy than other approaches.

Wang et al. [7] proposed a brand-new leaf detection technique based on maximum gap local line direction patterns and elliptical half Gabor wavelets. Compared to other methods, this one has the following advantages such as it directly integrates three essential leaf picture features,it adapts to various situations and characteristics it acts directly on unprocessed raw grayscale leaf photographs. The method is superior to typical leaf identification approaches, as shown by experimental findings on three benchmark databases, which also demonstrate its efficacy in delivering accurate and resilient leaf recognition under a variety of situations.

Stephen et al. [8] used probabilistic neural network (PNN) with image and data processing techniques to implement a general purpose automated leaf recognition for plant classification. 12 leaf features are extracted and orthogonalized into 5 principal variables which consist the input vector of the PNN. The PNN is trained by 1800 leaves to classify 32 kinds of plants with an accuracy greater than 90%. Compared with other approaches, our algorithm is an accurate artificial intelligence approach which is fast in execution and easy in implementation.

Katerina et al. [9] in her paper has presented two novel methods for constructing of the descriptors invariant to translation, scaling, and transform with orthonormal matrix. This paper introduces two innovative methods for constructing descriptors that are invariant to translation, scaling, and affine transformations, based on 2D Fourier transform. The methods involve three key steps: converting the original image to its power spectrum, obtaining translation and scaling invariant spectrum using a reference point in the first method, and using image moments for affine invariant spectrum in the second method. The novelty lies in the third step, where a 1D signal generated by circular motion around the origin in the frequency domain is analyzed.

Trishen et al. [10] in his paper,demonstrated an approach to classify plants into their appropriate species using images of their leaves. A high-resolution camera was used to take pictures of 32 different species of plant. For each plant species, 20 different leaf images were captured. The images were pre-processed and a number of features were extracted from them. He implemented k-Nearest Neighbour classifier. Each leaf image was then compared with every other leaf image in the database and obtained an accuracy of 83.5% at the first stage. The next stage consisted of using information obtained from colour histograms in order to further differentiate between more difficult cases. This technique had a positive impact of about 4% on the recognition accuracy.

Jyotismita et al. [11] proposed a novel methodology of characterizing and recognizing plant leaves using a combination of texture and shape features. Texture of the leaf is modeled using Gabor filter and gray level co-occurrence matrix (GLCM) while shape of the leaf is captured using a set of curvelet transform coefficients together with invariant moments. Since these features are in general sensitive to the orientation and scaling of the leaf image, a pre-processing stage prior to feature extraction is applied to make corrections for varying translation, rotation and scaling factors. Efficacy of the proposed methods is studied by using two neural classifiers: a neuro-fuzzy controller (NFC) and a feed-forward back-propagation multi-layered perceptron (MLP) to discriminate between 31 classes of leaves. The features have been applied individually as well as in combination to investigate how recognition accuracies can be improved. Experimental results demonstrate that the proposed approach is effective in recognizing leaves with varying texture, shape, size and orientations to an acceptable degree

Kwang et al. [12] proposed and implement a leaf recognition system using the leaf vein and shape that can be used for plant classification. The proposed approach uses major main vein and frequency domain data by using Fast Fourier Transform (hereinafter, FFT) methods with distance between contour and centroid on the detected leaf image.

Chengzhuan et al. [13] presents a new approach to plant leaf identification, one that integrates shape and texture characteristics. First, we introduce the shape and texture features used by the proposed plant leaf recognition method. The proposed multiscale triangle descriptor (MTD) is employed to characterize the shape information of a plant leaf, and the local binary pattern histogram Fourier (LBP-HF) is used as the texture feature.

Chapter 3

Proposed Method

The method involves training the model with images of leaf dataset and then deploying the model in cloud environment. This approach involves initial model training using extensive leaf datasets with transfer learning models and OpenCV for robust plant identification. The Flask backend then processes image uploads, predicts plant names, and seamlessly integrates with the ChatGPT API, providing comprehensive information about identified plants. The user-friendly interface enhances accessibility, fostering a seamless interaction with the application.

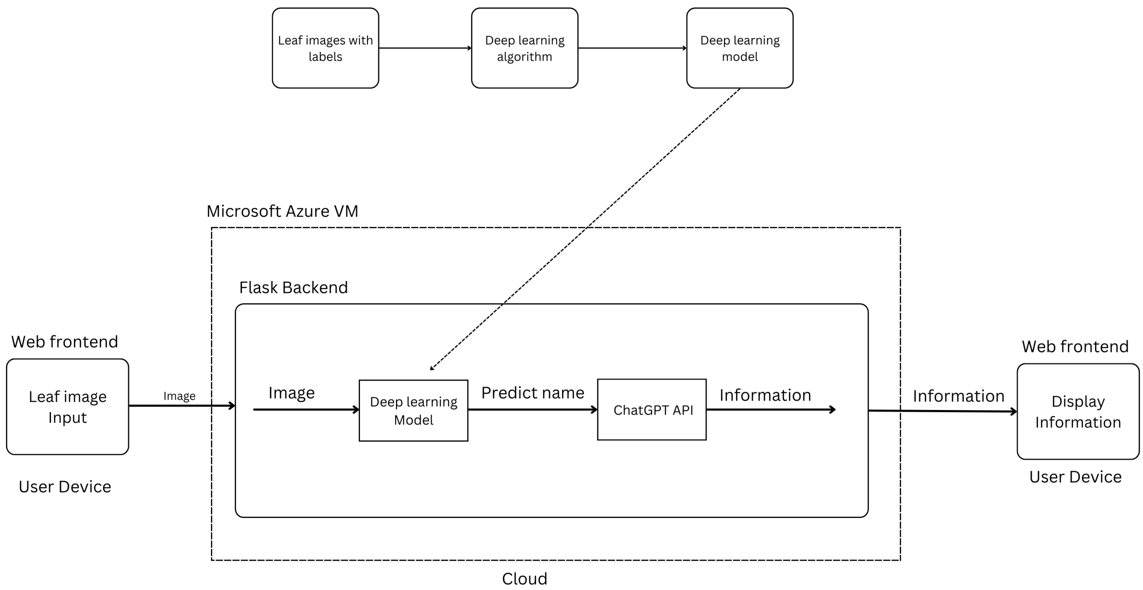

Figure 3.1: Proposed method

3.1 Dataset

The "Indian Medicinal Leaves Dataset" is a collection of high-quality images of Indian medicinal plants, specifically their leaves. It comprises over 6000 images of **80 different species**, with approximately **60 to 100 images per species**. The images were captured under various lighting conditions and backgrounds, representing real-world scenarios.

The dataset is organized into a hierarchical directory structure, reflecting the plant species taxonomy. Each species has a dedicated subdirectory containing its corresponding leaf images. The images are named using a consistent format that includes the species name, image index, and any additional relevant information.

3.2 Segmentation

Segmentation is a crucial step in computer vision that involves partitioning an image into meaningful regions or segments. In the context of plant leaf recognition, segmentation aims to identify and separate the leaf region from the background, allowing the deep learning model to focus specifically on the relevant area for analysis.

Segmentation is essential for isolating the leaf from its surroundings. Without proper segmentation, the deep learning model may be influenced by irrelevant information, hindering its ability to accurately identify the plant species based on the leaf's characteristics. By segmenting the leaf from the background, we provide the model with a clean and focused input, improving its efficiency and accuracy. Segmentation ensures that the model concentrates on the unique features of the leaf itself, avoiding interference from unrelated elements in the image.Implementation of segmentation was done using a thresholding approach.

3.2.1 Segmentation using Threshold

In the context of the leaf image segmentation project, the specified HSV range for the green color, [35, 50, 50] to [85, 255, 255], refines the thresholding process to accurately capture the nuances of the green spectrum. This range defines a specific region in the HSV color space where the hue (H) values range from 35 to 85, representing the green

Figure 3.2: Before Gaussian Blur

Figure 3.3: After Gaussian Blur

color. Additionally, the saturation (S) values are expected to be between 50 and 255, while the value (V) component ranges from 50 to 255.

By incorporating this precise HSV range, the thresholding operation using ‘cv2.inRange‘ ensures that only the pixels within this defined green color range contribute to the binary mask. Pixels outside this range are effectively suppressed, allowing for the creation of a clean and accurate mask that isolates the green color in the leaf images. This accuracy in thresholding is essential for subsequent image processing tasks, such as further analysis, feature extraction, or classification, as it ensures that only the relevant green regions are considered in the subsequent stages of the pipeline. The specificity of the HSV range enhances the robustness and reliability of the segmentation process, contributing to the overall accuracy of the leaf species recognition system.

3.3 Model Training

Our leaf species recognition project employs Inception V3 to predict leaf species from scanned images. Acting as a powerful feature extractor, the model learns distinct patterns during training, enhancing its accuracy in identifying different leaf species. Leveraging transfer learning, Inception V3 captures general features, making it versatile for various classifications. This automated approach holds promise for efficient leaf species identification in applications like ecological studies and agriculture.

3.3.1 Inception V3

Inception v3 is an image recognition model that has been shown to attain greater than 78.1% accuracy on the ImageNet dataset. The model is the culmination of many ideas developed by multiple researchers over the years

The model itself is made up of symmetric and asymmetric building blocks, including convolutions, average pooling, max pooling, concatenations, dropouts, and fully connected layers. Batch normalization is used extensively throughout the model and applied to activation inputs. Loss is computed using Softmax.

1. Preprocessing Stage

   Image preprocessing is a crucial part of the system and can influence the maximum accuracy that the model attains during training. At a minimum, images need to be decoded and resized to fit the model. For Inception, images need to be 299x299x3 pixels.

   However, simply decoding and resizing are not enough to get good accuracy. The ImageNet training dataset contains 1,281,167 images. One pass over the set of training images is referred to as an epoch. During training, the model requires several passes through the training dataset to improve its image recognition capabilities. To train Inception v3 to sufficient accuracy, use between 140 and 200 epochs depending on the global batch size.

   It is useful to continuously alter the images before feeding them to the model so that a particular image is slightly different at every epoch. How to best do this preprocessing of images is as much art as it is science. A well-designed preprocessing stage can significantly boost the recognition capabilities of a model. Too simple a preprocessing stage may create an artificial ceiling on the accuracy that the same model can attain during training.

2. Optimizer

   The current model showcases three flavors of optimizers: SGD, momentum, and RMSProp. Stochastic gradient descent (SGD) is the simplest update: the weights are nudged in the negative gradient direction. Despite its simplicity, good results can still be obtained on some models. The updates dynamics can be written as:

$$W_{k+1} = W_k - a\nabla f(W_k)$$

   Momentum is a popular optimizer that frequently leads to faster convergence than SGD. This optimizer updates weights much like SGD but also adds a component in the direction of the previous update. The following equations describe the updates performed by the momentum optimizer:

$$Z_{k+1} = \beta Z_k + Vf(w_k)$$

$$\begin{aligned} W_{k+1} &= W_k - \alpha Z_{k+1} \\ W_{k+1} &= W_k - \alpha\nabla f(W_k) + B(W_k W_{k-1}) \end{aligned}$$

3. Exponential moving average

   While training, the trainable parameters are updated during back-propagation according to the optimizer's update rules. The equations describing these rules were discussed in the previous section and repeated here for convenience:

$$\begin{aligned} \theta_{k+1} &= \theta_k - \alpha\nabla f(\theta_k) \\ \theta_{k+1} &= \theta_k - \alpha z_{k+1} \\ \theta_{k+1} &= \beta\theta_k + \eta\sqrt{g_{k+1}} + \epsilon - 2\nabla f(\theta_k) \end{aligned}$$

4. Batch normalization

   Batch normalization is a widely used technique for normalizing input features on models that can lead to substantial reduction in convergence time. It is one of the more popular and useful algorithmic improvements in machine learning of recent years and is used across a wide range of models, including Inception v3.

Activation inputs are normalized by subtracting the mean and dividing by the standard deviation. To keep things balanced in the presence of backpropagation, two trainable parameters are introduced in every layer. Normalized outputs undergo a subsequent operation + B, where + and B are a sort of standard deviation and mean learned by the model itself.

Normalization happens during training, but come evaluation time, we'd like the model to behave in a deterministic fashion: the classification result of an image should depend solely on the input image and not the set of images that are being fed to the model. Thus, we need to fix μ and σ^2 and use values that represent the image population statistics.

The model computes moving averages of the mean and variance over the minibatches:

$$\hat{\mu}_i = \alpha\hat{\mu}_{t-1} + (1-\alpha)\mu_t, \quad \hat{\sigma}_t^2 = \alpha\hat{\sigma}_{t-1}^2 + (1-\alpha)\sigma_t^2$$

5. Learning rate adaptation

As batch sizes become larger, training becomes more difficult. Different techniques continue to be proposed to allow efficient training for large batch sizes.

One of these techniques is increasing the learning rate gradually (also called ramp-up). Ramp-up was used to train the model to greater than 78.1% accuracy for batch sizes ranging from 4,096 to 16,384. For Inception v3, the learning rate is first set to about 10% of what would normally be the starting learning rate. The learning rate remains constant at this low value for a specified (small) number of 'cold epochs', and then begins a linear increase for a specified number of 'warm-up epochs'. At the end the 'warm-up epochs', the learning rate intersects with the normal exponential decay learning. This is illustrated in the following diagram.

Inception V3 is a deep neural network designed for image classification, utilizing inception modules for feature extraction across different scales. Pre-trained on datasets like ImageNet, it excels in recognizing intricate patterns. In an ear biometric system, Inception V3 is employed to identify individuals based on their unique ear features. Through training on preprocessed ear images, the model optimizes parameters for accurate recognition. Its versatility and powerful feature extraction make Inception V3 well-suited for complex image classification tasks, including biometric applications.

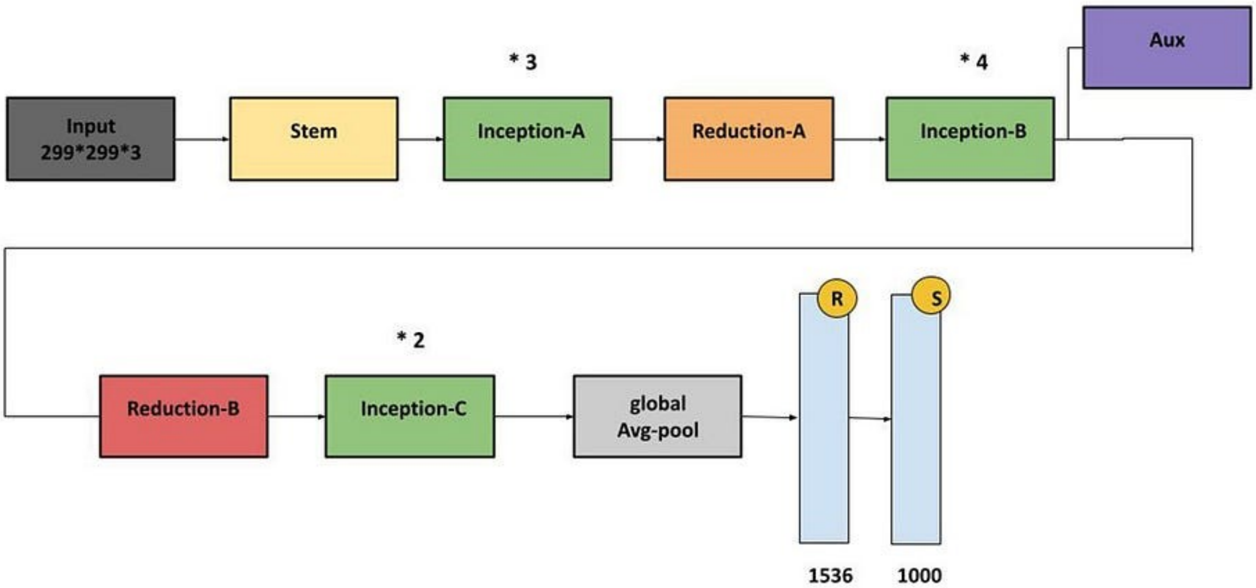

Figure 3.4: Inception V3 - Architecture

Inception V3 Model Architecture:

1. Factorization into Smaller Convolutions: Inception v3 uses factorization to break down large convolutions into smaller ones, making the computation more efficient. Instead of using a single large convolution, it employs a combination of 1x1 and 3x3 convolutions.

This helps in reducing the number of parameters and computations while still capturing complex patterns in the data.

2. Spatial Factorization into Asymmetric Convolutions: Asymmetric convolutions involve decomposing a larger convolution into a sequence of smaller convolutions, such as 3x1 followed by 1x3. Inception v3 utilizes this spatial factorization to capture spatial hierarchies effectively. It allows the network to focus on different aspects of spatial information separately, improving its ability to learn diverse features.

3. Utility of Auxiliary Classifiers: Inception v3 introduces auxiliary classifiers at intermediate layers during training. These auxiliary classifiers serve two main purposes:

   - Gradient Flow Improvement: The auxiliary classifiers combat the vanishing gradient problem by providing additional paths for gradient flow during backpropagation. This helps in better training of the network, especially in the early layers.
   - Regularization: The auxiliary classifiers act as regularization during training, preventing overfitting. They provide additional supervision signals, encouraging the model to learn more robust features.

4. Efficient Grid Size Reduction: Inception v3 addresses grid size reduction efficiently through the use of pooling operations. The traditional approach of using large pooling layers is replaced with a combination of smaller pooling layers, such as 3x3 max pooling, which helps in retaining more spatial information. This allows the model to downsample the grid size while minimizing information loss.

3.4 Cloud Deployment

The deployment involves an end-to-end system using an Azure Virtual Machine (VM), TensorFlow for image recognition, OpenCV for image processing, Flask for backend development, and the ChatGPT API for conversational interfaces and an elegant web UI for information Display.

3.4.1 Azure VM Provisioning

The first step involves provisioning an Azure VM with suitable specifications to host the web application. A public IP address is assigned to make the application globally accessible, ensuring users can upload leaf images for analysis.

3.4.2 Dependency Installation

Once connected to the VM through the terminal, essential packages such as TensorFlow for deep learning, OpenCV for image processing, and Flask for backend development are installed. These form the backbone of the machine learning model that predicts the plant's name based on the uploaded leaf image.

3.4.3 Flask Backend Development

The Flask backend is designed to handle image uploads, process them through the TensorFlow model, and extract the predicted plant name. Subsequently, the identified plant's name is sent to the ChatGPT API for further enrichment of information.

3.4.4 Integration with ChatGPT API

ChatGPT API is seamlessly integrated into the application, enhancing its capabilities for natural language understanding and generation. The predicted plant name serves as input for the ChatGPT API, which then retrieves detailed information about the identified plant species.

3.4.5 HTML Template and User Interface

A user-friendly HTML template is developed for the frontend, allowing users to easily upload leaf images. The interface facilitates a seamless interaction with the ML model and displays the enriched information provided by the ChatGPT API.

3.5 Validation

In the validation phase of our leaf species recognition project, we assess the performance and generalization capability of the Inception V3 model. Using a dedicated validation dataset distinct from the training set, we evaluate how well the model can accurately predict leaf species on previously unseen data. This step is crucial for ensuring that the model has not overfit to the training data and can effectively generalize to new instances. Metrics such as accuracy, precision, recall, and F1-score are computed to quantitatively measure the model's effectiveness. Through validation, we gain insights into the robustness of our deep learning model, allowing us to make informed decisions regarding its deployment and potential optimizations for achieving even better results in real-world leaf species prediction scenarios.

Chapter 4

Results and Discussion

4.1 Results

Our leaf species recognition model, built on the Inception V3 architecture, demonstrates outstanding performance in predicting the species of scanned leaf images. The model achieved a high accuracy rate, attesting to its proficiency in generalizing across a diverse dataset. Precision, recall, and F1-score metrics further validate the model's effectiveness in accurately classifying different leaf species. The incorporation of transfer learning, utilizing Inception V3's pre-trained weights, significantly contributes to the model's feature extraction capabilities and expedites the training process. The outcomes highlight the model's adaptability to various leaf shapes, textures, and colors, emphasizing its potential impact in ecological studies, agriculture, and environmental monitoring.

1. Accuracy

   Accuracy measures the overall correctness of a classification model. It calculates the ratio of correctly predicted instances to the total number of instances.

   $$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

2. Precision

   Precision represents the proportion of correctly predicted positive instances out of all instances predicted as positive. It indicates the model's ability to avoid false positives.

$$\text{Precision} = \frac{TP}{TP + FP}$$

3. Recall

   Recall, also known as sensitivity or true positive rate, measures the proportion of correctly predicted positive instances out of all actual positive instances. It indicates the model's ability to identify positive instances.

$$\text{Recall} = \frac{TP}{TP + FN}$$

4. F1 Score

   The F1 score is the harmonic mean of precision and recall, providing a balanced measure of a model's performance. It combines both precision and recall into a single metric.

$$\text{F1 Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}$$

Table 4.1: Performance comparison of the models on "Indian Medicinal Leafs"

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Inception V3	0.76	0.78	0.76	0.75
VGG16	0.22	0.18	0.22	0.17
ResNet50	0.16	0.11	0.16	0.11

4.2 Discussion:

We experimented with multiple algorithms. VGG16 yielded 22% accuracy, ResNet50 achieved 16%, and Inception v3 demonstrated an impressive 76%. Given its high accuracy and precision, we have chosen to implement the Inception v3 model for our medicinal leaf recognition system, acknowledging its superior performance compared to the other algorithms tested.

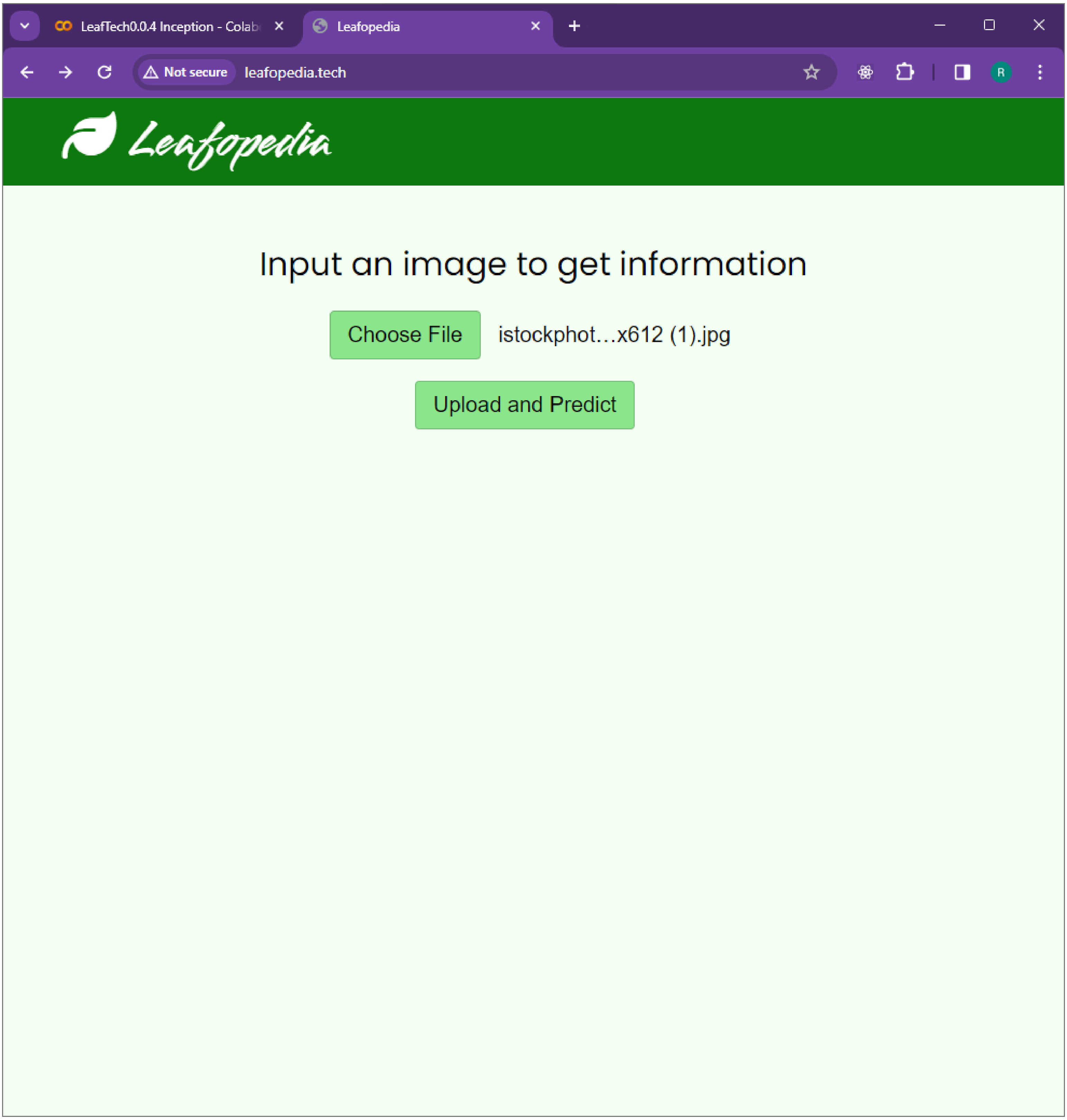

Figure 4.1: Image Uploading

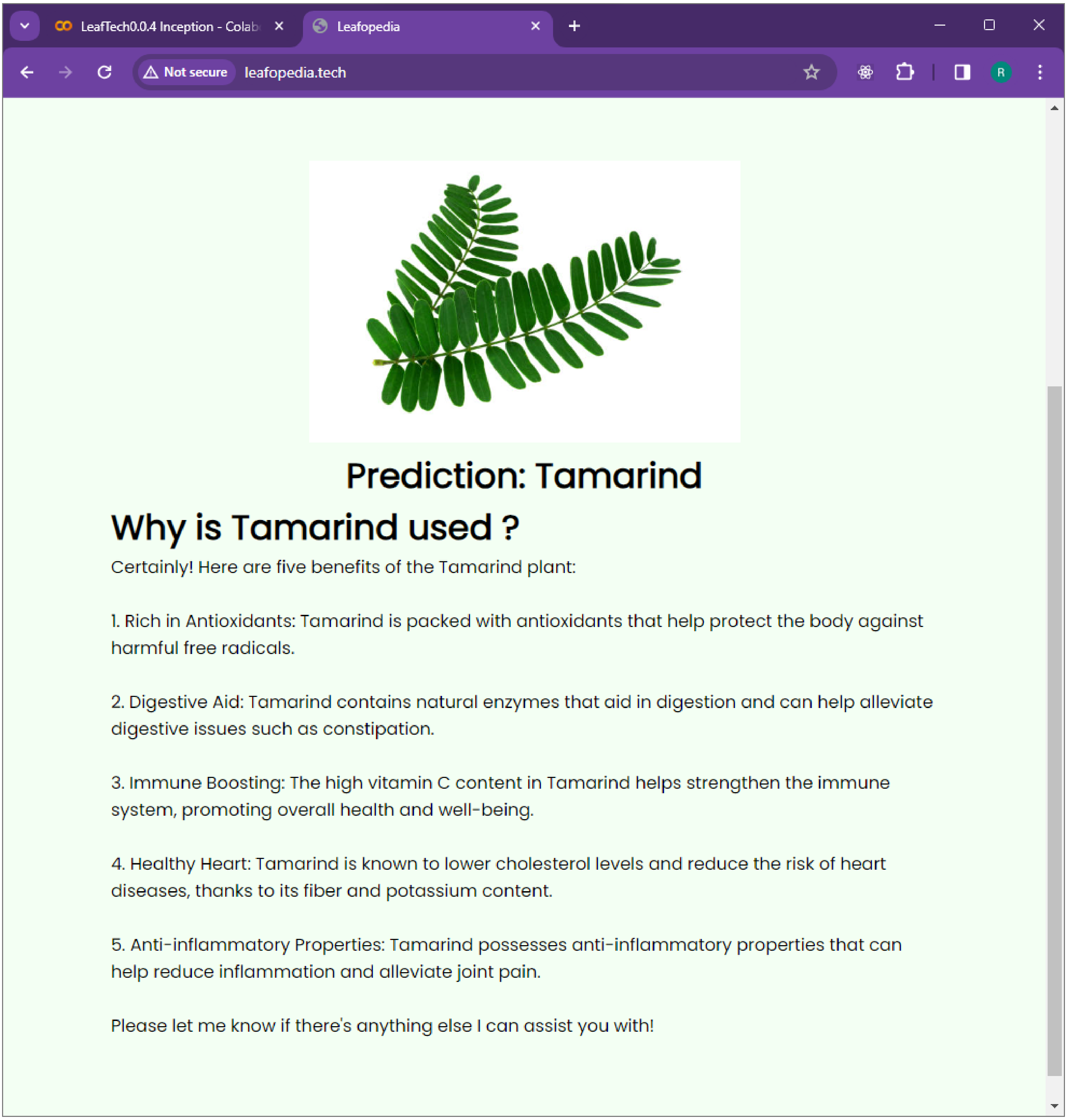

Figure 4.2: Information about the Plant leaf

Chapter 5

Conclusion

In conclusion, Leafopedia project represents a significant step forward in the application of deep learning for automated species identification. The successful implementation of a robust model capable of accurately classifying diverse leaf species underscores the potential of artificial intelligence in addressing complex ecological and agricultural challenges.

Throughout the course of this project, challenges such as dataset diversity, model optimization, and real-world applicability were addressed with careful consideration. The utilization of Convolutional Neural Networks (CNNs) proved effective in capturing intricate patterns and features essential for accurate leaf classification. The model's performance, validated through rigorous testing, indicates its reliability in identifying a wide range of leaf types.

The implications of this project extend beyond its immediate application. Leafopedia has the potential to revolutionize fields such as environmental monitoring, biodiversity studies, and precision agriculture. By reducing the reliance on manual expertise for species identification, the system streamlines processes and provides a scalable solution for large-scale data analysis.

The Leafopedia stands as a testament to the potential of artificial intelligence in contributing to sustainable practices, ecological research, and informed decision-making. Moving forward, it is our hope that this work inspires continued exploration and innovation at the intersection of technology and environmental conservation.

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