

Research Article

Automated Plant Recognition System with Geographical Position Selection for Medicinal Plants

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Received 9 August 2022; Revised 1 February 2023; Accepted 11 February 2023; Published 23 March 2023

Academic Editor: Zhongxu Hu

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Basically, it is hard for endeavors to recognize plant leaf images by a layman due to the varieties in some plant leaves and the extensive information collected for investigation. It is hard to build an automated recognition framework that can handle massive data and give an intermediate analysis. Image examination and order and pattern recognition are some issues that are effectively connected to the existing methods. This paper focuses on designing an automated plant recognition system based on the best recognition algorithm and the Google platform to locate all plant locations on a map. A case study of India, which has huge biodiversity, is illustrated. The proposed system can show the detailed location of that particular species, where they can be found, and the shortest distance from the current location.

1. Introduction

One of the most basic sorts of life on our planet is a plant that helps to maintain a balance between O₂ and CO₂ in the earth's atmosphere [1]. An automated plant recognition framework is useful in the greenhouse to save stop administration, new plant species revelation, plant scientific classification, and extraordinary plant location [2]. A plant distinguishing system or characterization framework utilizes distinctive attributes of greenery, beginning at an extremely straightforward level (such as shape and shade of leaf, bloom, and natural product sort, expanding style, root sort, regularity, and viewpoint) to an exceptionally complex level [3]. This kind of system has been investigated by many researchers as an effective tool for the identification of plants [4].

It is necessary to design a system for recognizing individual plants of a selected type growing in a field based on

each pixel of image data [5]. Various image segmentation methods have been proposed for the identification of plants from an image. Classification based on leaf image is the first choice for plant recognition [5]. The leaf image is transferred to a computer to extract features automatically using image processing techniques. However, creating an automated plant recognition system based on the best abovementioned algorithms is as necessary as locating all plant locations on a map using the Google platform. This article aims to propose such a system using descriptive algorithms so that other readers can utilize it for plant recognition. A summary of the related works is also taken into account in this paper.

The proposed system is experimentally tested in the case study of India, where colossal biodiversity is observed [6]. A wide range of flora and fauna can be found in the Indian subcontinent, but the problem comes when it comes to identifying the species and when there is a need to locate them geographically on a map [7]. The Indian subcontinent

has a wide variety of plants. It is estimated that 6-7% of the total world flora is present in India alone. Amazingly, 45,000 different species of plants are found in India, many of which are endemic [8]. It is officially documented that more than 3000 species of these plants are medicine plants [9].

Wu et al. [10] separated twelve regularly utilized advanced morphological components into five principal features utilizing principal component analysis for 1800 leaves to arrange 32 types of plants [6]. A centroid contour distance curve, eccentricity, and angle code histogram were used to shape leaves in a meta-physics-based leaf grouping framework [11]. Han et al. proposed the cubic interpolation local binary pattern (CILBP) and dbN wavelets for grass identification based on leaf images [12].

A depending on the leaf pictures, an effective plant species recognizable proof approach was proposed in [8]. Gu et al. [13] utilized the aftereffect of the division of the leaf's skeleton given the mix of wavelet transformation (WT) and Gaussian interpolation. Wang et al. [7] separated geometric components such as rectangularity, circularity, capriciousness, and seven-minute invariants for categorization. They presented a strategy for perceiving leaf pictures in light of shape features utilizing a hyper circle classifier. Some authors utilized an artificial neural system and the K-Nearest neighbour (K-NN) classifier to characterize plants. Du et al. [8] presented shape acknowledgment given the outspread probabilistic neural system.

The arrangement of minute invariants for rotation, translation, and scaling reasonably for the acknowledgment of items with fold rotation symmetry was presented in [14]. Chan et al. [15] dealt with the move of the median centers hypersphere classifier in light of advanced morphological components. A viable method for plant species was executed on the plants with wide-level leaves [16]. Another system for highlight extraction from the regular picture-like plant leaf was produced by Kaya et al. [17] for robotized living plant species recognizable proof, which is helpful for plant understudies to do their examination for plant species distinguishing proof. Kadir et al. [18] constructed a foliage plant distinguishing proof framework for 60 sorts of leaves. Zernike minutes were joined with geometric features, color moments, and a gray-level cooccurrence matrix. The authors used the consequences of trials in enhancing the execution of leaf recognizable proof framework utilizing principal component analysis (PCA) to change over the elements into orthogonal outcomes that were put as an input in the probabilistic neural network (PNN) classifier [19]. This approach has been tried on 2 datasets, Foliage and Flavia, which individually contain different shading leaves (foliage plants) and green leaves. The outcomes demonstrated that PCA can build the precision of the leaf identification framework on both datasets.

Rashad et al. [17] acquainted an approach to plant arrangement given the portrayal of texture properties. Bhardwaj and Kaur [20] concisely depicted different plant acknowledgment procedures, and Bhardwaj et al. [21] dealt with arranging plant leaf pictures on the premise of higher-request minute invariants and texture examination utilizing

the K-NN classifier. Lü et al. [16] audited a hypothetical foundation on how contrasts in hereditary structure might be produced through procedures that are an inalienable factor over space. After that, completion with a concise survey of how spatial investigation has added to the preservation and utilization of plant hereditary assets through comprehension of spatial examples in species circulation and hereditary structure. Du et al. [8] proposed a productive approach called Computer-Aided Plant Species Identification (CAPSI) which depends on pictures of plant leaves utilizing a shape-coordinating strategy.

Cassidy [22] identified the preservation advantages and expenses of distinctive generation frameworks that control species protection in nature or the nursery. Wang et al. [7] introduced another arrangement of minute invariants for the interpretation, turn, and scaling reasonably to acknowledge items having fold rotation symmetry. Minute invariants cannot be utilized because most snapshots of symmetric articles vanish. Their freedom and fulfillment were demonstrated hypothetically. Selvam et al. [4] proposed a proficient arrangement system for leaf pictures with a complex foundation. Söukand and Kalle [23] researched the possibility of a natural scene related to an individual view of the scene as a wellspring of material medicine. The home-grown scene can be separated into particular littler units as per a few typical and social limits. Hou et al. [24] were expected to give a rundown of medicinal plants and offer essential information for additional contemplates on these herbs from Tibet. Minaee et al. [25] presented a straightforward and computationally proficient strategy for plant species acknowledgment utilizing leaf pictures. This technique works for plants with expansive-level leaves. Jia et al. introduced the application design of AI image recognition in power systems [26]. Lv et al. designed the deep learning model for image classification [27].

Hossain et al. [28] proposed a novel structure for perceiving and recognizing plants utilizing shape, vein, shading, and surface components consolidated with Zernike developments. Radial basis probabilistic neural network (RBPNN) has been used as a classifier. To prepare RBPNN, the authors utilized a double-stage preparation method, which fundamentally improves the execution of the classifier. Reproduction comes about in the Flavia leaf dataset, showing that the proposed strategy for leaf acknowledgment yields an exactness rate of 93.82%. Adeel et al. [29] designed an automated system based on the saliency approach and multiple-feature fusion for diagnosing and recognizing grape leaf diseases. Wang and Goudos [30] proposed a faster R-CNN for multi-class fruit detection using a robotic vision system. Dwivedi et al. [31] developed a leaf disease detection mechanism. It is based on an L1-norm minimization extreme learning machine.

This article is organized into five sections. In Section 2, summaries of related works are highlighted, both in terms of advantages and disadvantages. Section 3 illustrates the proposed system and algorithms to identify medicinal plants and locate them on a map. The results of the software are discussed in Section 4. Lastly, Section 5 concludes the research article and elaborates on further studies.

1.1. Motivation. The motivations behind considering the current work as our research challenge are summarized as follows:

- (i) With the increasing prices of allopathy medicines, herbal medicines are gaining more attention than their conventional counterparts.
- (ii) An increasing collection of scientific evidence demonstrates the efficiency of medicinal herbs and the dosages at which they are effective, even though they may not be as potent or as quickly acting as conventional medicine. Most of the time, they have fewer side effects than traditional prescriptive medicines.
- (iii) But the difficulty of obtaining ingredients is a significant disadvantage of using indigenous medicine. By destroying forests, industrialization and deforestation have made it more difficult to find herbs and medicinal plants. However, there have been numerous attempts to widen access to therapeutic herbs.

1.2. Contributions. The significant contributions of the proposed solution toward identifying medicinal plants with geographic location selection are as follows:

- (i) It uses an effective leaf-shape-based feature extraction method to identify the medicinal plant on an emergency basis.
- (ii) Helps taxonomists develop a more efficient species recognition framework which will protect endangered species and make the local population aware of the discoveries and their usage in real-time scenarios.

2. Related Works

Table 1 indicates the comparative study for different parameters used in the existing literature, and Table 2 indicates the comparative studies with their advantages and disadvantages. In Table 1, twelve related methods are compared. Table 2 shows that improvement in terms of the leaf image-based feature extraction algorithm's optimization and efficiency are much needed in further studies. However, existing approaches lack robust solutions, which have been attempted to be addressed in our proposed system through productive characterization and simple usage for application in real-time scenarios.

3. The Proposed System

The system was tested with three approaches and implanted as an android-based mobile App "Manthan" to recognize the medicinal plants. It also locates the nearest required plant. This helps identify medicinal plants which cure diseases by the Ayurvedic method and make medicines. Based on the medicine plants considered, the proposed system is divided into three different approaches as follows:

3.1. Approach 1: Morphological Algorithm-Based Nearest Plant Detection. The idea is to make a mobile-based App that has an appropriate solution. Recognition of the medicinal leaves is done using OpenCV. At first, the characteristics of the leaf-like edge, color, area, texture, and shape are extracted using a neural network morphological algorithm in OpenCV. Later, the user's image can be matched with the data in the database to give the best result. With the plant details, we also upload the latitudes and longitudes (geographical locations) where those are found. During a search, an algorithm finds the nearest plant location and the way to it from the user's device for locating it on the map using Google APIs. The processing steps of the morphological algorithm-based nearest plant detection are described in Algorithm 1.

3.2. Approach 2: Support Vector Machine (SVM)-Based Nearest Plant Detection. The flow of work remains almost the same. The recognition of the medicine leaves has been done by Python. At first, we resized the image as desired. Then we convert this RGB image to grayscale. Later, the user's image can be matched with the data to give the best result. SVM is used as we have a small dataset. Android Studio is used to design the application. The processing steps of the support vector machine-based nearest plant detection are described in Algorithm 2.

3.3. Approach 3: Image Processing-Based Nearest Plant Detection. Another way of doing the same task is by doing image processing and classifying the leaves in MATLAB. The processing steps of the image processing-based nearest plant detection are described in Algorithm 3.

The abovementioned three approaches are useful only when Internet connectivity is present at a sufficient level. Apart from that, we have to consider the version compatibility issue of Open CV, as its working mechanism varies with version changes. The time constraint of OpenCV due to the library import process gets addressed while using Python, but the Python server gets costly with the increased code complexity. The image processing approach done in MATLAB overcomes the issues of the previously taken two approaches. The nntools algorithm has worked efficiently, and the Google API based on minimum distance finding has achieved satisfactory accuracy in fetching the nearest location of the species during the search process.

The user has two options: upload the image to be identified and get the location of the species by entering its name. Both of the above pieces of information that have to be maintained by the administrator are indicated in Figure 1.

As shown in Figure 2, the administrator has to upload the sample image of the species, the locations where it is found, and the characteristics a particular species of plant has, and that includes the morphological details. But biological details like their uses and scientific names cannot be uploaded.

TABLE 1: Comparative study for different parameters.

No.	Authors	Techniques/parameters
1	Gu et al. [13]	Geographic information systems, functional genomics and improved quantification of adaptive traits, spatial analysis, and genotype-environment interactions
2	Galappathie et al. [6]	Dynamic programming
3	Cassidy [22]	Domestication
4	Wang et al. [7]	Complex moments
5	Kadir et al. [32]	Probabilistic neural network
6	Hossain and Amin et al. [28]	Image segmentation
7	Hou et al. [24]	Ethnobotany
8	Kulkarni et al. [33]	Tibetan traditional medicine
9	Fu et al. [11]	Leaf identification
10	Han et al. [12]	Leaf identification
11	Bhardwaj et al. [20]	Plant classification
12	Lü et al. [16]	Convexity, leaf identification system, PCA, PNN, solidity
13	Kaya et al. [17]	Zernike moments and gray-level-co-occurrence matrix

TABLE 2: Advantages and disadvantages of the comparative studies.

No.	Authors	Advantages	Disadvantages
1	Kadir et al. [32]	Utilized probabilistic neural network with picture and information preparing procedures to execute broadly useful robotized leaf recognition for plant categorization	Need further improvement
2	Galappathie et al. [6]	Leaf pictures utilizing a shape-coordinating method	Need to consolidate distinctive elements (for example, texture or shading highlights)
3	Hossain and Amin [28]	A productive categorization system for leaf pictures with entangled backgrounds is proposed	Requires more concentration on the most proficient method to characterize and process the leaf picture many-sided quality and join level set strategy with the watershed procedure to enhance the division impact of leaf pictures with the confounded background
4	Wang et al. [7]	Introduced another arrangement of minute invariants for revolution and interpretation	Need robust solutions
5	Fu et al. [11]	Displayed a straightforward and computationally effective technique for plant species acknowledgment utilizing leaf pictures	It required client help in the pre-preparing stage and failed to work with pictures with entangled backgrounds
6	Lü et al. [16]	Revealed consequences of analyses in enhancing the execution of leaf identification framework utilizing principal component analysis	Possibly utilizing some other strategy may acquire much better execution
7	Bhardwaj and Kaur [20]	The capacity to characterize and perceive the plant from a little piece of the leaf without depending neither on the state of the leaf nor on its shading highlights since the framework relies upon the textural highlights	Need to apply statistical pattern acknowledgment techniques which contemplate commotion
8	Gu et al. [13]	Given knowledge on how examining topographic examples may add to an enhanced comprehension of fluctuation in genetic structure	Notwithstanding a set of hypotheses about how versatile genetic structure may fluctuate over space and along natural slopes, tests have tended to concentrate on basic and controlled cases to test the speculations
9	Cassidy [22]	Recognizing the protection advantages and expenses of the diverse creation frameworks for MAP should help direct approaches	There is a need to perceive and reinforce the part of nearby individuals in woods stock, check and affect evaluation forms, and coordinate non-timber items utilized in backwoods administration. Additionally, there is a requirement for the usage of administration design and the need for eco-labeling and certification
10	Kulkarni et al. [33]	This means a rundown of therapeutic plants	Need further pharmacological studies
11	Hou [24]	Investigated the possibility of a natural scene related to an individual view of the scene as a wellspring of material medicine	Ought much consideration to be paid to the root of the information of plant use, as it might assume an urgent part in the ID of the plant and may comprehend the view of a natural scene in specific areas and the populace, all in all too
12	Kaya et al. [17]	Suggested a unique system for perceiving and distinguishing plants utilizing shape, vein, shading, and texture elements joined with Zernike developments	A negative part of Zernike minutes is their expensive computation, making them incompetent for a few issues

Step 1: Images of the leaf are taken with a high-resolution camera.
 Step 2: The images are converted to jpeg format to process them to extract information.
 Step 3: Android Studio integrated with OpenCV libraries is used as a platform to develop the application.
 Step 4: Using OpenCV, the program is coded in Java to extract all leaf details like edge, color, area, texture, and shape. This is done using a neural network morphological algorithm.
 Step 5: The image data is uploaded to the database with other information and the importance of the plant.
 Step 6: For each plant species, geographical locations in the form of latitude and longitude are stored in a database. If complexity arises in matching, further analysis can be done using prediction algorithms. The locating is done by creating a database consisting of all the latitudes and longitudes for each specific species, and then it is queried to show the geotags through Google Maps. This can be done by passing the values in arrays in a function.
 Step 7: Google API is used to fetch the nearest location of the species during a search using minimum distance algorithms.

ALGORITHM 1: Morphological algorithm-based nearest plan detection.

Step 1: Images of the leaf are taken with a high-resolution camera.
 Step 2: The images are converted to jpeg format to process them to extract information.
 Step 3: Android Studio is used as a platform to design the application, and coding can be coded in any editor like Atom. Python has to be installed in the system.
 Step 4: The image is first cropped to a specific size as that of the size of our dataset.
 Step 5: It is then converted to grayscale.
 Step 6: A comparison is made with all the leaves from the dataset using the SVM or tools algorithm.
 Step 7: The image is uploaded to the database with other information and the importance of the plant.
 Step 8: For each plant species, the geographical locations in the form of latitude and longitude are to be stored in a database.
 Step 9: Google API is used to fetch the nearest location of the species during a search using minimum distance algorithms.

ALGORITHM 2: SVM-based nearest plant detection.

4. System Illustration

During development, dependencies may occur to create the database with the support of external sources such as image analysis experts/image processing tools. We may take the help of any tools/components for the identification of geographical locations. An image was captured using a 5 MP mobile camera. Then, the image is resized to 64×64 . The cropped image is converted to the greyscale image and compared with those in the dataset to give the best approximate value as the desired output. The details are fetched as queries from the database when searching through the text field. Figure 3 shows the home screen of the application.

One example of searching species names by the designed application is shown in Figure 4. In Figure 4(a), the name of the plant to be searched is inputted. Then, the search result of the plant is shown in Figure 4(b). In this example, *Quercus Suber* is searched by its name, and the resultant image of *Quercus Suber* is shown in Figure 4(b). The example of searching by location by the designed application is shown in Figure 5. In Figure 5(a), the desired location is inputted. Then, the search result is shown in Figure 5(b). In this

example, *Quercus Suber* is searched by its location, and the location image of *Quercus Suber* is shown in Figure 5(b).

In addition, the search option shows the location of species on a map by the designed application in Figure 6. When choosing a search image, an image can be selected from the gallery, which is then searched and matched against the images available of species in our database. The search result is shown as the species name, with other details in Figure 5.

Figure 7 shows the list of characteristics used in the proposed system so that the classification of images can be done to increase the accuracy of search results. Here, some characteristics such as botanical name, parts used, and medicinal use are included. Figure 8 shows the locations of the searched species located on the map by the designed application. In this example, three locations of the search species have been shown on the map. It also shows the nearest locations of the species from the current location. Figure 9 shows the extra features of the designed application, like some websites and databases. Figure 9(a) shows the features of the website. In addition, the features of the database are shown in Figure 9(b).

Step 1: Images of the leaf are taken with a high-resolution camera.
Step 2: The images are converted to jpeg format to process them to extract information.
Step 3: Android Studio is used as a platform to design the application. MATLAB has to be installed in the system.
Step 4: The image is first cropped to a specific size as that of the size of our dataset.
Step 5: It is then converted to grayscale.
Step 6: A comparison is made with all the leaves from the dataset using the SVM or nntools algorithm.
Step 7: The image data is uploaded to the database with other information and the importance of the plant.
Step 8: For each plant species, the geographical locations in the form of latitude and longitude are to be stored in a database.
Step 9: Google API is used to fetch the nearest location of the species during a search using minimum distance algorithms.

ALGORITHM 3: Image processing-based nearest plant detection.

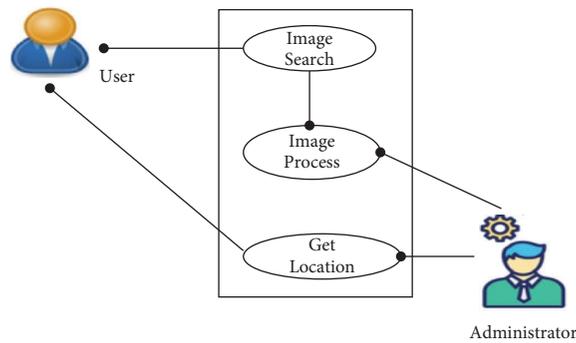


FIGURE 1: User and administrator interconnection.

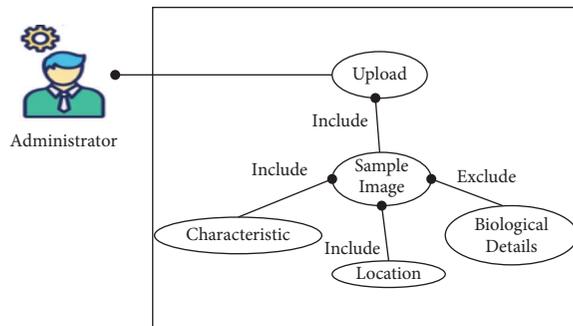


FIGURE 2: Information allowed and disallowed to be uploaded by the administrator.

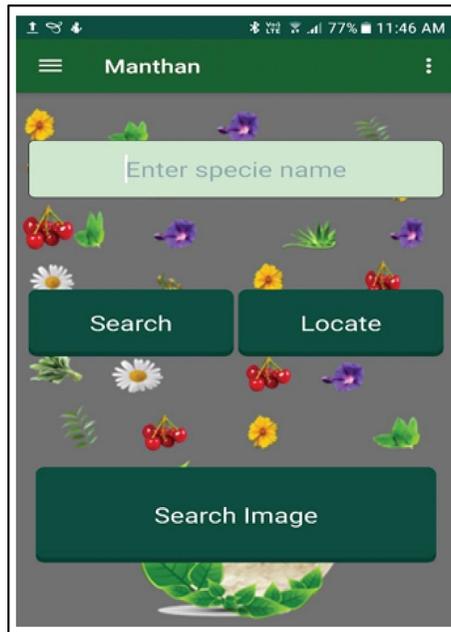


FIGURE 3: Home screen of the designed application.

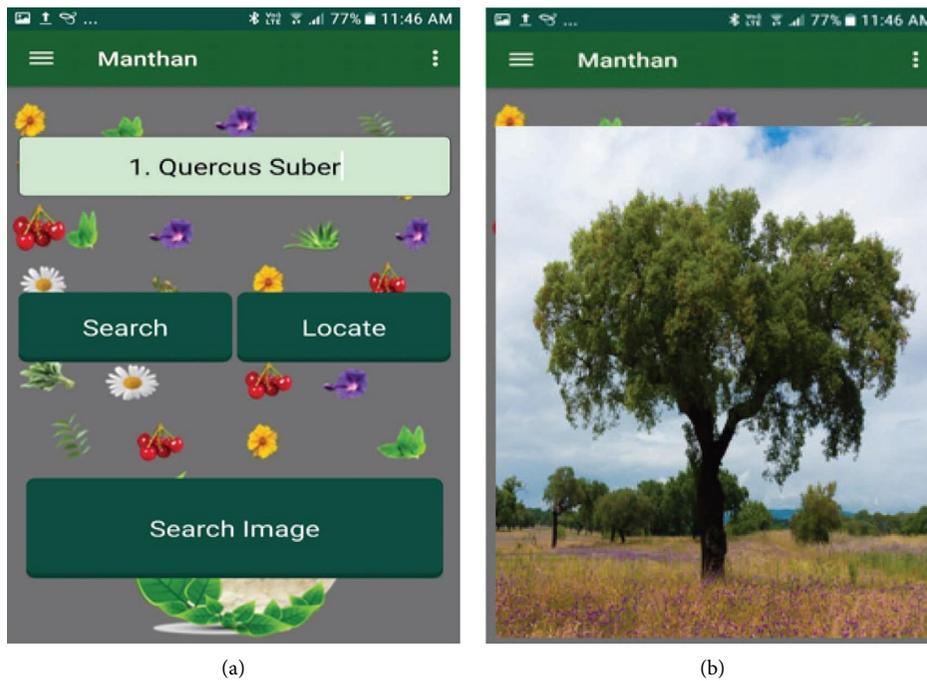


FIGURE 4: Example of the searching plant by name. (a) Input the name. (b) The search result.

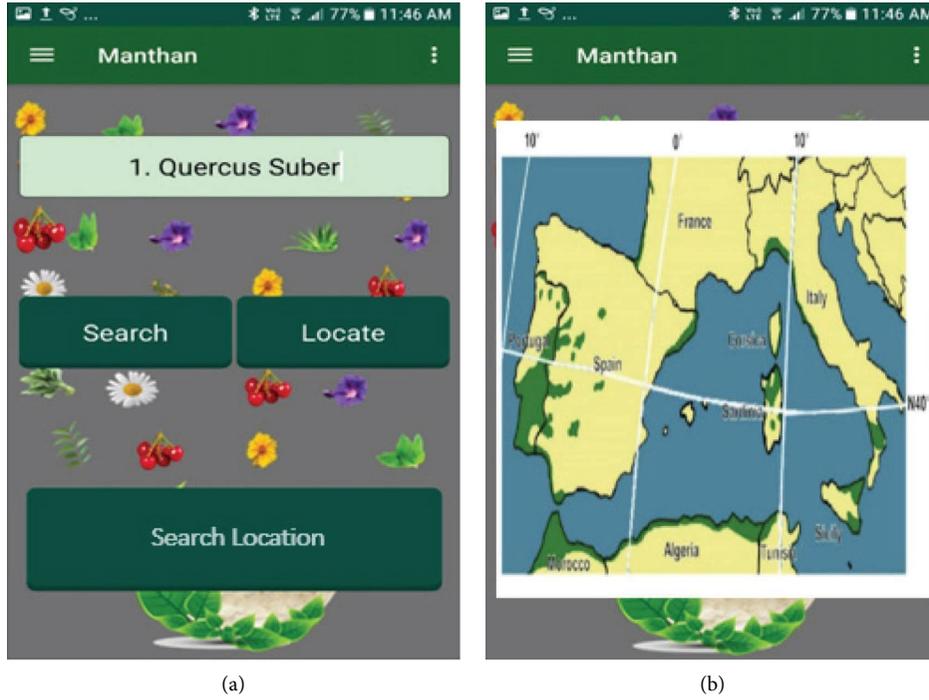


FIGURE 5: Example of the searching plant by location. (a) Input the location. (b) The search result.

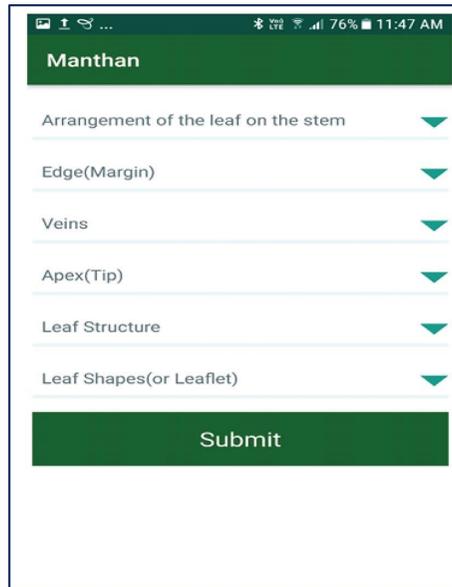


FIGURE 6: Different options after login.



FIGURE 7: List of characteristics.

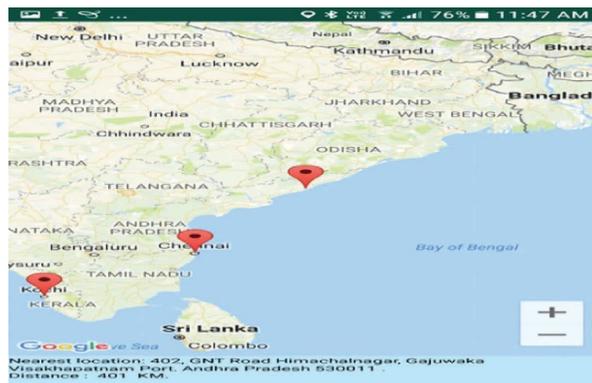


FIGURE 8: Locations of the searched species on the map.

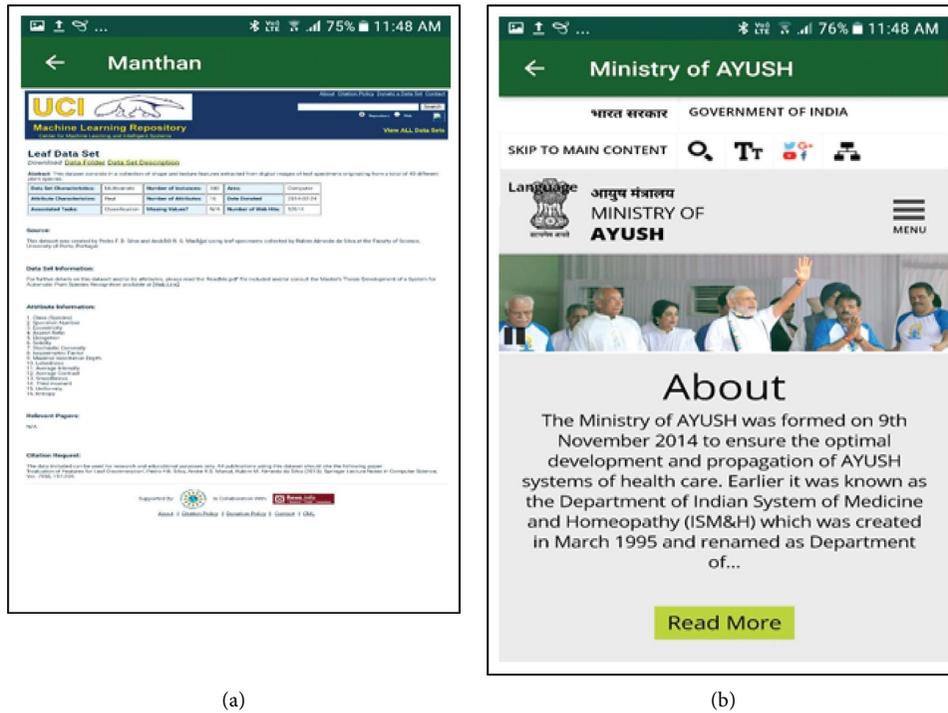


FIGURE 9: Extra features of the designed application. (a) Website. (b) Database.

5. Conclusions

In this paper, we develop a new framework for plant recognition on a map. It is easy to implement and has a productive characterization as well as simple usage. An effective and streamlined arrangement procedure was utilized to speed up the application for real-use scenarios. The proposed system works through mobile interfaces. It gives details of many plants and how they can be used. If any individual is not within reach of first aid, the fruitful results generated by this system can help overcome fatigue. Also, we know that few diseases have been cured only through Ayurveda. The proposed mobile-based application can show the detailed location of that particular species, where they can be found, and the shortest distance from the current location.

The proposed system works entirely on the Internet. Thus, Internet connectivity is a must for efficiently working the application. Integration of OpenCV is quite difficult as its procedure varies greatly between different versions. A Python server is costly. Further extensions are also possible for this paper through acknowledgment strategies that contemplate commotion and more plant databases. Innovative technology is being made possible by the rapid increase in Internet usage and the digitalization of various businesses. The lighting sector is undergoing revolutionary change and is increasingly embracing light fidelity and the Internet of Things. Wi-Fi radiation can hurt sensitive areas like medicinal plant recognition, but installing Light Fidelity in these locations can offer a faster and safer alternative. In the near future, we will try to integrate software-defined visible light networking into our proposed solution.

Data Availability

The data that are used to support the conclusions of this research are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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