Using image recognition artificial intelligence to identify different types of plants, and the practical applications of this technology

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Abstract

Plant identification could be seen as a subject just for botanists and biologists. However, that is not the case, computer scientists have taken an interest in this subject as shown by the copious amount plant identification applications currently available to the public. These applications create a user-friendly environment in which users can identify specific types of plants through various methods. From answering a series of simple questions about the plants identifiable characteristics to simply taking a picture of a plant and being told within seconds what that plant is, this solution can be implemented in so many ways. The algorithms used to achieve the correct identification vary from each application, and these different algorithms affect how accurate the resulting identifications are.

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# Exploration of the problem

Due to the current climate in the world, many species of plants are starting to become extinct due to changes in their environment. “Current rates of species loss triggered numerous attempts to protect and conserve biodiversity. Species conservation, however, requires species identification skills, a competence obtained through intensive training and experience” (Wäldchen, Rzanny, Seeland, Mäder, “Automated plant species identification—Trends and future directions” 2018). These plants going extinct is not the only affect this has on the environment, it is damaging the biodiversity of areas and in turn affecting the populations of animals who inhabit those areas. “Plant researchers, botanists, and scientists identify a particular plant species by looking at the texture, shape, color of the leaves, flowers, fruits, or other parts of the plant. However, it is difficult for those who are unfamiliar with all the plant species to perform this identification. For instance, trekkers and botany students might find a plant species in rarely-visited areas but be unable to identify the rarity of the plant. This causes many potentially-rare plants to remain undiscovered in the wild, impeding plant conservation efforts.” (Chavan, Ford, Yu, Saniie,” Plant Species Image Recognition using Artificial Intelligence on Jetson Nano Computational Platform” 2021) It is critical that we improve upon this technology as it could be used to assist in stopping the extinction of more plants and animals.

# Background Information

To understand how this technology works it is important to have a basic understanding of artificial intelligence and image recognition algorithms.

## Artificial Intelligence

Artificial intelligence is now so ingrained in our technology that it is so easy to overlook. “Artificial Intelligence can drive cars, trade stocks and shares, learn to carry out complex skills simply by watching YouTube videos, translate across dozens of different languages, recognise human faces with more accuracy than we can, and create original hypotheses to help discover new drugs for curing disease.” (Dormehl, “Thinking Machines” 2016)

Due to how varied AI technology can be that description gives little hints to what it is and how it works. Artificial intelligence (AI) is the term used to describe technology that has been created to have some level of intelligence by human definition. This can be many different things; these technologies range from the facial recognition software many smartphones now use as a form of security to chatbots that many companies use as a replacement for human ran customer service. (Last Name, Year)

## Image Recognition

AI can also be trained to recognise images. Computers can’t recognise images the way that we can. Facial recognition software is a great example of this. Computers can’t comprehend faces in the same way we do, but we can train them to be able to identify notable features of faces and can even train them to create their own faces. An amazing example of this is https://thispersondoesnotexist.com/ when an AI generates a new face every time the webpage is refreshed. None of the people pictured are real people however they are very convincing. This AI has been fed images of real people and trained to use the data that it learned about human faces to create new ones. Most of the time you could not tell that the face is created by an AI.

## Turing Test

Alan Turing devised a test now referred to as the Turing test, that calls for two entities to communicate with each other; one a machine and the other a person. The point of this test is to determine how intelligent(human) the machine can behave. This test is applied to things like chatbots, so how do we measure how intelligent image recognition artificial intelligence is?

The measure of accuracy for type of image recognition AI we are discussing is simply by dividing the number of successfully identified images by the total number of images given to identify. Most of the time this resulting fraction is then converted into a percentage.

## Implementation

Now that we have an understanding of why these technologies are so important, we can discuss the different methods of implementation and the positives and negatives of each one.

### Neural Networks

Neural networks are networks that take inspiration from how the human brain works. Neural networks take in data and train themselves to recognize patterns in this data. They train themselves by splitting the process into different layers. There are three main layers in neural networks, the input, the hidden layer, and the output. The input is simply the data that the neural network is fed, and the output is the result the neural network puts out. The input layer takes the image the neural network has been given and splits it up into each pixel. This is because computers cannot perceive images in the same way that people do, they can only perceive images by each pixel and the colour data related to it. The hidden layer is where the training happens. The hidden layer uses a function called the activation function that is a calculation that makes use of the weight –which is used to decide how much influence each part of the input- and the bias -that is a constant value used to shift the value of the activation function. There are many different calculations for the activation functions that can be used for different situations. The goal of the activation function is to identify what parts of the input are important and are likely to identify the input to give us the most likely output. To be able to have the neural network assign weights and biases the neural network must be trained on what we want it to identify. Training a neural network requires feeding it input and the corresponding output. The more input and output the neural network are given the more likely it is to correctly identify the output. This is often referred to as supervised learning.

### Identification using full images

One method of implementation is to simply create an ai and train it by giving it a data set of images of plants with accompanying labels indicating what type of plant is pictured. This method tends to be popular with many mobile applications that are currently available, as it is simple to implement. This method is not ideal as no matter how extensive the training data is as it is harder to consider factors such as plants that appear identical but differ on small aspects that aren’t reflected in the images used for training data. This affects the accuracy of the identifications, meaning the algorithm is less likely to correctly identify an image.

### Identification using distinguishing features

This seems to be the most advantageous method of plant identification. “Most researchers use variations on leaf characteristic as a comparative tool for studying plants, and some leaf datasets including Swedish leaf dataset, Flavia dataset, and ICL dataset are standard benchmark.” (Sun, Liu, Wang, Zhang “Deep Learning for Plant Identification in Natural Environment” 2017) It makes a lot of sense as it is a human way of identifying something. The idea of taking a unique feature and using it to identify something is what many humans do naturally. This method doesn’t work well with only one image of the whole plant for identification as ideally the user would need to give a few pictures of defining pictures such as the leaves and/or flowers.

# Review of current work

The market for these applications is growing as the popularity of house plants rises and they become more accessible. Searching up plant identification on google play or the app store will give you hundreds of results.

### British Trees

The Woodland Trust have an application available to the public called “British Trees” the application allows users identify different British trees by asking a series of questions about specific characteristics of the trees. This application does not use any form of artificial intelligence or image recognition. However, that does not make this application any less beneficial.

The application makes use of notable features to identify different species of tree. Features such as leaf shape and colour, fruit and flowers allow for easy identification of different types of trees and breaks down the problem of identifying a tree into a smaller and easier to solve problem.

This method appears to be an ideal starting point, so to test how accurate this method of identification is I asked a group of users to participate in a survey. The users were asked to download the British Trees mobile application and use it to identify different trees from images provided. Out of the ????? people who took this survey ?????? were able to correctly identify all four of the test images provided. This gives us an accuracy of ????????%. The accuracy was calculated by dividing the number of successfully identified trees by all attempts made to identify the trees.

By conducting this survey, I was able to find out how accurate this is from a human standpoint. I found the margin for human error in this application very large as the majority of the time users were getting very different identifications. Many users reported finding the application difficult to use, despite the simple interface, as the application did not give one specific identification for many trees, instead it gave the users many different options and they were left to decide the correct result by themselves.

One user commented on the fact that the application asked for the specific colours of leaves and berries. The user was colour blind and found it difficult to determine what colour the characteristics were so ended up with the wrong identification. This brings up the idea of accessibility. For this type of application to be truly accessible it needs to be automated. Not all users have the ability to identify creatin characteristics as displayed by this user’s difficulty.

**Deep Learning for Plant Identification in Natural Environment**

In 2017 Yu Sun, Yuan Liu, Guan Wang, and Haiyan Zhang published a paper titled “Deep Learning for Plant Identification in Natural Environment” where they explored the different methods to implement plant identification systems. They used the Beijing Forestry University (BJFU 100) dataset that consisted of 10,000 images of 100 plants from the Beijing Forestry University campus. “The BJFU100 dataset is collected from natural scene by mobile devices. It consists of 100 species of ornamental plants in Beijing Forestry University campus. Each category contains one hundred different photos acquired by smartphone in natural environment.” (Sun, Liu, Wang, Zhang, “Deep Learning for Plant Identification in Natural Environment” 2017) Figure.1 displays an example of one of the images used in this dataset. This is an example of identification using a whole image rather than identification through distinguishing characteristics. As the images are taken in the “natural environment” this has the capability to make the identifications less accurate, as computers cannot differentiate between the subject and the background without additional training. This is an important problem to overcome especially for this specific project as the aim to have a mobile identification application, and many users won’t be able to capture an image without a background.

This paper discusses how “The model implementation is based on the open source deep learning framework keras” (Sun, Liu, Wang, Zhang, “Deep Learning for Plant Identification in Natural Environment” 2017). According to the Keras website it is “a deep learning API written in Python, running on top of the machine learning platform TensorFlow.” (Keras, 2021).

To train this algorithm the dataset was split so for each example 80 of the images were used for training and the other 20 were used for testing. This allows there to be no overlap in testing, as testing the algorithm on images it has been trained on would not be a valid and reliable test.

“The proposed model achieves a recognition rate of 91.78% on the BJFU100 dataset.” (Sun, Liu, Wang, Zhang, “Deep Learning for Plant Identification in Natural Environment” 2017). This software is promising; however, the writers note that “Although the research on automatic plant taxonomy has yield fruitful results, one must note that those models are still far from the requirements of a fully automated ecological surveillance scenario” (Sun, Liu, Wang, Zhang, “Deep Learning for Plant Identification in Natural Environment” 2017). Which is unfortunately still true, but this technology is rapidly advancing.

**iNaturalist.org**

iNaturalist.org was founded in 2008 by a group of university students from California. The group announced the launch of a website that would be able to identify both plants and animals automatically. The website originally allowed “Users upload a photo, and the community of experts and amateur citizen scientists help identify it – but according to their website, “on average, observations take 18 days to be identified by the community, with half of all observations identified in the first two days.”” (Nemire, “AI App Identifies Plants and Animals In Seconds” 2017) However, the team decided that that put too much stress on those who were doing the identifications and recruited students from Cornell Lab of Ornithology to create an application that would be able to identify these plant and animal species faster.

“Using NVIDIA GPUs and cuDNN with the TensorFlow deep learning framework, they trained the neural networks on their massive database of images that have been labeled by the site’s community of experts. Currently, they are able to identify 10,000 different species and are adding new species to the model every 1.7 hours.” (Nemire, “AI App Identifies Plants and Animals In Seconds” 2017)

**Artificial Intelligence for plant identification on smartphones and tablets**

In 2020 Hamlyn G Jones put out a paper detailing tests done on different mobile plant identification applications. The tests were done using “38 contrasting plant images of wild and naturalised British species (including grasses, sedges, herbs and woody plants as well as on images of flowers, leaves, fruits or whole plants), largely selected from my own visual-flora website (visual-flora.org.uk). The samples included a number of common species, some garden escapes and several less common or even rare species (e.g. Cyperus fuscus). Each image was tested five times with each app because many apps gave surprisingly variable identifications even when using exactly the same image. All tests were conducted in October or November 2019, but many of the apps are continually improving.” (Jones, “What plant is that? Tests of automated image recognition apps for plant identification on plants from the British flora” 2020) These images are depicted in Figure 2. we can see that they are clear images where we can see the plant or a notable characteristic of the plant. The background is the natural setting for these plants, which could cause the identification to be less accurate, but as these applications are mobile applications available to the general public it is important that this should not affect the accuracy too drastically.

The author stated that they “found it very difficult to predict in advance of tests which images were or were not going to be identified successfully” (Jones, “What plant is that? Tests of automated image recognition apps for plant identification on plants from the British flora” 2020) This can be the case with many of these applications, as we don’t know what happens in the hidden layers for the majority of the time and so it is hard to predict what the results will be. Hence test plans made for these systems need to be flexible and it is unlikely you are able to fully predict what the outcomes will be.

Many of the mobile applications used don’t explicitly state what training data set they use or even what type of algorithm they use so it is hard to fully compare them, on a technical basis. However, it is still useful to evaluate the accuracy of these applications, as it allows us to see the differences between them.

The method used to evaluate these mobile applications is not the traditional the number of correctly identified divided by all the those tested. Instead, the tests took into account many different factors such as the possibility for the same image to be given different identifications by the same application and what features the application was most likely to identify the plant correctly based off of. Whilst these are all interesting factors to take into account, we want to look at the overall accuracy. The table pictured in Figure 3. shows how accurately each application identified each plant. We can see that PlantID and Google lens were the most accurate, scoring 75.1% and 68.5% retrospectively. iNaturalists application, named Seek was third with an accuracy of 60.7%. None of these applications compare to the 91.78% accuracy that the algorithm created using the BJFU100 dataset did, but this can be down to many factors. These applications are made for mobile use therefor have hardware restrictions, where as it is not mentioned if the BJFU110 application was made to the same constrains. Also the testing of the BJFU100 algorithm could be have a bias as the images it was tested on came from the same dataset as it was trained on.

**Plant Species Image Recognition using Artificial Intelligence on Jetson Nano Computational Platform**

This paper discusses the importance of being able to rely on artificial intelligence for plant identification. “Traditional plant identification approaches are both expensive and time-consuming since they require manual intervention by human experts. Machine learning algorithms are useful but still take longer amounts of time and yield poorer results as compared to deep learning methods.” (Chavan, Ford, Yu, Saniie,” Plant Species Image Recognition using Artificial Intelligence on Jetson Nano Computational Platform” 2021)

The technology developed in this paper makes use of the LeafSnap dataset that is composed of 23,147 of 185 plants. The images are of the leaves from each plant on a white background. This indicates that this technology is made to recognize the plant by specific features just as people do. “Training data collected with a simple background often provides better results. Orientation and illumination restrictions were not put on the lab images dataset.” (Chavan, Ford, Yu, Saniie,” Plant Species Image Recognition using Artificial Intelligence on Jetson Nano Computational Platform” 2021)

This technology is created using a deep learning artificial intelligence algorithm, which is a blanket term that includes neural networks where the algorithm gives weights and biases to the input to increase the accuracy of its attempt at identification. “Deep learning architectures, such as deep neural networks, deep belief networks, and recurrent neural networks, have been applied to fields such as computer vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation, bioinformatics, drug design, medical image analysis, material inspection, and board game programs, where they have produced results comparable to, and in some cases superior to, human experts.” (Chavan, Ford, Yu, Saniie, ”Plant Species Image Recognition using Artificial Intelligence on Jetson Nano Computational Platform” 2021)

To test the algorithm used the authors used a dataset of 15 “randomly chosen” plant types with 30 images for each plant taken from the LeafSnap dataset. The author admits that this testing dataset is on the smaller side due to time constraints so this could affect the reliability of the tests. Displayed in Figure 4. we can see the difference in accuracy between the test and the validation accuracy. This proves to us that due to the small testing dataset the test was not as thorough as they could be. Thorough testing is important with this kind of system as the aim is to give the most accurate identification possible.

**Automated plant species identification—Trends and future directions**

In 2018 a paper was published titled “Automated plant species identification—Trends and future directions”. It discusses many factors in the identification of plants and the surrounding technology.

The process of training a machine learning algorithm can be seen in Figure 5. “From a machine learning perspective, plant identification is a supervised classification problem” (Wäldchen, Rzanny, Seeland, Mäder, “Automated plant species identification—Trends and future directions” 2018) This is the idea of supervised learning discussed earlier. The idea that the computer is given the question and the answer to allow it to form conclusions about the relationships between the question and answer to allow the computer to determine the answer itself when only given the question in the future. This type of machine learning is used for many plant identification applications as it helps to train it to identify the image.

The idea of model-free approaches is discussed in this paper. Model-free approaches follow the idea that model-based approaches are limiting and aim to overcome them. “They do not employ application-specific knowledge and therefore promise a higher degree of generalization across different classes, i.e., species and their organs.” (Wäldchen, Rzanny, Seeland, Mäder, “Automated plant species identification—Trends and future directions” 2018)

“In contrast to model-based and model-free techniques, CNNs do not require explicit and hand-crafted feature detection and extraction steps. Instead, both become part of the iterative training process, which automatically discovers a statistically suitable image representation (similar to a feature vector) for a given problem” (Wäldchen, Rzanny, Seeland, Mäder, “Automated plant species identification—Trends and future directions” 2018) CNNs, short for convolutional neural networks are a from of neural network that specialize in processing image data that has been separated into pixels that contain colour data. They tend to have a similar structure to neural networks, but it is more complicated. The hidden layer has a layer called the convolution layer. The convolution layer is the main layer in a CNN, and it makes use of the kernel that is a set of learnable parameters. The kernel is used to produce a 2-dimensional(2D) image referred to as the activation map. This activation map is used to determine the class of the image. CNNs are a great way to create this type of learning algorithm with the aim to classify images.

Many applications make use of the leaf shape to determine what type of plant it is being asked to identify. However, this can be limiting as it only works for plants that can be distinguished by their leaf shape. In reality there are many other factors that the developers of these technologies are not taking into account. This paper discusses many of them, such as leaf texture and colour, flower shape and colour, how flowers grow on the plants and the formations that the flowers grow in. The amount of these identifiable characteristics is huge, and they can be incredibly beneficial in identification. However, the question is where to draw the line, what is important and could aid toward identification and what is simply unnecessary? We need to take into account that many plants only flower or grow fruit at certain times of year, how will these plans be identified when not growing flowers or fruit. These are all factors that must be considered and there are not many definitive answers for these questions currently, as the need for these technologies is only growing as climate change is affecting the environment and the plants that are integral to the biodiversity of areas.

# Conclusion

These applications can be used in many different situations by many different users. They have the potential to be incredibly beneficial in the first step to preserve species of plants that are becoming extinct. However, currently the idea of simply snapping one picture on a mobile phone and getting an accurate identification one hundred percent of the time might be a bit farfetched. In reality, just as people need more than one image to correctly identify a plant, AI needs more to give an accurate identification. Studies have show that using multiple different images that depict distinct features of plants are far more likely to give a correct identification, and whilst there isn’t an algorithm that has a one hundred percent accuracy, this is the closest we have currently.

References

Wäldchen, Rzanny, Seeland, Mäder, “*Automated plant species identification—Trends and future directions*” 2018

Chavan, Ford, Yu, Saniie, “*Plant Species Image Recognition using Artificial Intelligence on Jetson Nano Computational Platform*” 2021

Jones, “*What plant is that? Tests of automated image recognition apps for plant identification on plants from the British flora*” 2020

Nemire, “*AI App Identifies Plants and Animals In Seconds*” 2017

Sun, Liu, Wang, Zhang, “*Deep Learning for Plant Identification in Natural Environment*” 2017

Figure 1:

A picture containing tree, outdoor, sky, plant

Description automatically generated

Figure 1.

(Sun, Liu, Wang, Zhang, “Deep Learning for Plant Identification in Natural Environment” 2017)

An image of a Chinese Buckeye from the BFU 100 dataset

Figure 2:

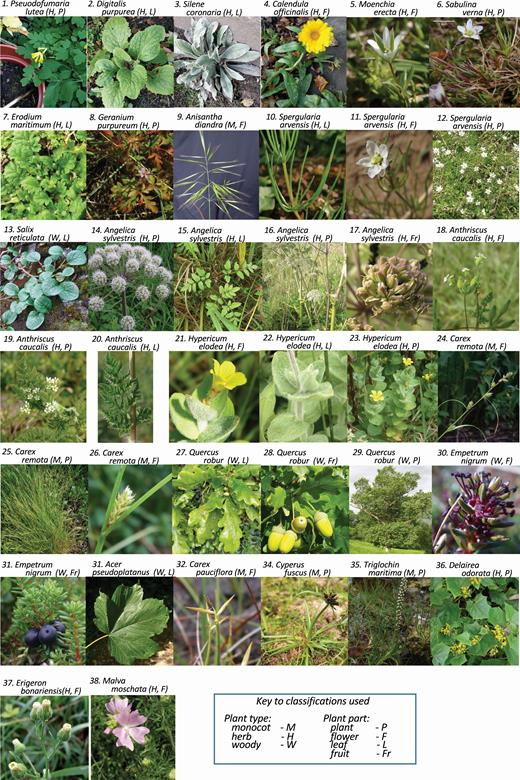


Figure 2.

(Jones, “What plant is that? Tests of automated image recognition apps for plant identification on plants from the British flora” 2020)

The images used to test various free to use mobile plant identification applications

Figure 3:

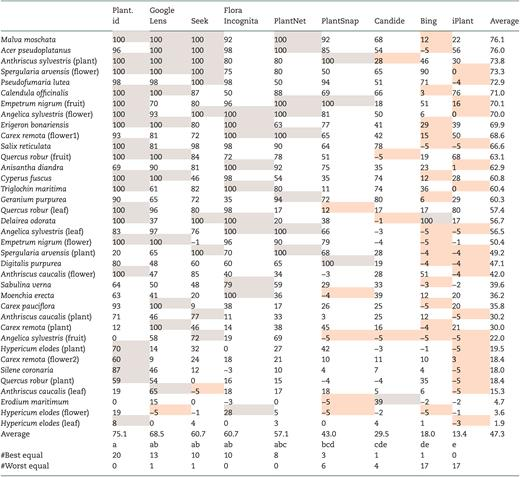


Figure 3.

(Jones, “What plant is that? Tests of automated image recognition apps for plant identification on plants from the British flora” 2020)

The table with the overall results for each application

Figure 4:

Table

Description automatically generated

Figure 4.

(Chavan, Ford, Yu, Saniie,” Plant Species Image Recognition using Artificial Intelligence on Jetson Nano Computational Platform” 2021)

A table displaying the results from testing the CNN using the LeafSnap dataset

Figure 5:

Diagram

Description automatically generated

Figure 5.

(Wäldchen, Rzanny, Seeland, Mäder, “Automated plant species identification—Trends and future directions” 2018)

A diagram depicting the process of training a machine learning algorithm