Evaluating Efficiency of Free Automated Plant Identification Applications

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Abstract

Professional ecologists and curious amateurs alike can benefit from the ease and speed of automated species identification using widely accessible and reasonably priced mobile phone applications, which eliminate the need for identification keys and field guides. It is commonly known that machine learning is becoming more accurate, but it is still unknown if and under what conditions free mobile phone applications can accurately identify plants to the species level in actual field settings. We use 875 properly recognized photos of 270 species from 200 genera to test five widely used and free plant identification programs. In all applications, 70% of images were accurately identified with the first proposal, and 86% of images were correctly identified in the top five choices. For each application, the kind of plant (woody, herbs, grasses, shrubs, ferns) significantly influenced identification performance. While exposure and focus were not crucial for certain applications, visual saliency was. Applications did a good job; at least one of the top three accurately identified 96% of the photos as their initial recommendation. We conclude that free phone-based plant identification applications are legitimate and helpful resources for anyone wishing to interact with nature and for those seeking quick identification, subject to some limitations.

Key Words: Mobile Phone Application, Machine learning, Plant Identification

INTRODUCTION

For management and conservation, ecological data are essential, especially for monitoring and surveying that supports interventions (Goodenough & Hart, 2017). Accurate species identification is essential since it is fundamental to know what species are present. However, identification can occasionally be very difficult, even for professionals (Bonnet et al., 2018). The need to understand field guides, identification keys, and the terminology used to identify specimens to species level may be a barrier to accurate data collection or to engaging with the natural world for non-professionals or inexperienced individuals (such as trainee ecologists, interested amateurs, and participants in citizen science partnerships) (Rehorek & Shotwell, 2018; Schussler & Olzak, 2008).

The COVID-19 pandemic saw a rise in public interest in nature (Grima et al., 2020; Soga et al., 2021; Tree, 2020; Venter et al., 2020), and the lockdown narrative frequently reflected this trend (e.g. Bevis, 2020; Stewart & Eccleston, 2020; Tree, 2020). Increased demand for information may be correlated with growing interest, and widely accessible and reasonably priced mobile phone applications provide quick and easy automatic species identification through well-known smartphone interfaces (Joly et al., 2014; Jones, 2020; Kaur & Kaur, 2019). There were documented increases in thedownloads of mobile phone applications related to bird identification (Associated Press, 2020) and bird call identification (Eurekalert, 2021), indicating that the use of these applications did indeed rise during the epidemic. Additionally, it is evident from Google Trends data that there was a surge in searches for "plant identification app" (Google Trends, 2021b) and "bird identification app" (Google Trends, 2021a) in May 2020, suggesting increased interest in these platforms. Compared to traditional field guides and identification keys, mobile phone applications may provide a quicker and simpler way to identify species (Joly et al., 2014; Jones, 2020; Kaur & Kaur, 2019). With user-selected settings limiting the potential species matches within a search framework, applications can be arranged similarly to a conventional taxonomic key. However, more and more programs or add-on devices employ machine learning-based automatic picture analysis or audio scanning to offer quick and easy identification recommendations for the target species (Jones, 2020; Robinson & Robinson, 2021).

Many commercially available applications now have automated identification capabilities thanks to significant advancements in automated recognition brought about by the development of deep learning and convolutional neural networks (LeCun et al., 2015) (Wäldchen & Mäder, 2018). The public's use of automated identification apps has grown recently, as evidenced by the high download rates of applications for mobile phones related to bird identification (Associated Press, 2020; Eurekalert, 2021) and the evident rise in searches for "plant identification app" and "bird identification app" (Google Trends, 2021a, 2021b). However, public acceptance does not always imply that the applications are ecologically sound, even though it may be significant for participation.

In a similar vein, Goëau et al. (2018) describe an experiment in which 19 distinct deep learning systems were tested using 10,000 plant photos in comparison to nine human experts: The automated systems obtained an accuracy of 88%. Using automated picture analysis with reference to an image library, deep learning frameworks can even be used to identify pollen on microscopes (Dunker et al., 2021). Commercially accessible plant identification applications have been directly evaluated against human specialists in other investigations. An "AI naturalist" created by August et al. (2020) looked for pictures of plants on Flickr. The program PlantNet (styled as Pl@ntNet) was then used to identify these pictures. Regarding pictures having a high "classification score" for PlantNet, While species level identification achieved about 70% accuracy, family and genus identification accuracy was both greater than 85%. Identification accuracy was significantly increased when a single plant was the main subject of the picture rather than being a component of a more complicated image.Jones (2020) used photographs of plant species from the United Kingdom that were chosen to be "as contrasting as possible" in order to assess the baseline accuracy of a few different applications. Although there were significant variations in accuracy between programs, the best ones were able to accurately identify at least 50% of the photos to genus.

Although nine applications were tested, the study did not take into consideration image parameters like focus (either in the optical sense or the sense in which August et al., 2020 used the term to indicate whether the floral subject was distinctive within the image), and the sample size of species and images was small (n = 38, with each image of a different species). In order to evaluate the Flora Incognita program, Mäder et al. (2021) asked two knowledgeable botanists to verify the identification that was returned for 1000 randomly chosen photos that were contributed by actual users. The botanists evaluated 847 of these photos and found that 787 (93%) of them were accurate. Pärtel et al. (2021) conducted additional testing on the Flora Incognita application and discovered that, in field settings, the program was 85.3% accurate, leading to better identification of photos including reproductive organs or only the target plant. Our understanding of the accuracy of plant identification applications that are available on mobile phones (and likely to be used in practice by ecologists and others seeking accurate identifications) is limited by small sample sizes (e.g. Jones, 2020) or a focus on single applications (e.g. August et al., 2020; Mäder et al., 2021; Pärtel et al., 2021), despite the fact that extensive tests of machine learning identification algorithms exist and confirm a high and improving level of accuracy. Here, we use 875 expertly recognised photos of 270 species from 200 genera to test the three well-known free plant identification apps for iPhone and Android smartphones: PlantNet, Floral incognita, and Platora.

Additionally, we evaluated Google Lens, a generic tool for photographic identification, and iNaturalist , a multi-taxon natural history program. After measuring overall performance in each instance, we looked into how different plant types (woody plants, flowering hebs, grasses, sedges and cryptogames) and image characteristics (optical focus, exposure, visual saliency) affected the accuracy of identification.

Methodology

A total of 10 students—all M.Sc Botany—were instructed to use their mobile phones' default settings to capture pictures of plants. Every participant provided written approval for the study to use their photos. Any vascular plant species found in the in the campus of Sangam University, Bhilwara, India, whether native or naturalised, were the target species. We omitted "exotic" species that are more likely to be found in planted parks and gardens because our main goal was to evaluate the efficacy of identification tools in the context of assisting ecology and conservation in the field. In order to shoot a "record shot," or a picture that captured the target clearly yet was taken rapidly in the field, participants were advised to adopt this mindset. Every single plant was only photographed once. Electronically supplied images were assigned a distinct file name. No photos were pre-processed, such as by cropping or modifying brightness or contrast settings, in order to simulate the true use of plant identification applications.
Four students independently scored each image to evaluate three aspects of image quality: focus (1–3 scale, with highest being best); exposure (underexposed = −1; correctly exposed = 0; overexposed = +1); and the dominance and clarity of the focal plant in the image, which is now referred to as "saliency" (Borji et al., 2015; 1–3 scale, with highest being best). To provide one value for each parameter per image, means were computed from individual scores. Additionally, one student evaluated each image to determine if a flower was visible (first binary variable). Whether a fruit was visible in the picture (third binary variable) and whether a leaf or other greenery was visible in the picture (second binary variable). For uniformity, the Botanical definitions were always employed when performing these evaluations, although the terminology used here are the general terms used within many plant identification tools, such as PlantNet and Plantora. Therefore, "flower" comprised any component of a flowering plant's flower structure, such as petals, sepals, sigma, and stamens, or any component of a grass, sedge, or rush's inflorescence; "leaf" included leaves (woody plants/herbal flowering plants). Stem/branches (cryptogames), blade (grasses), frond (ferns), and culm (sedges, rushes, and grasses); the term "fruit" was limited to woody and forb species because it referred to a swollen and ripening ovary. Each image's focal plant species was recognised by a minimum of two students. This was either one of the four students and the original photographer, who was also an ecological professional. After that, each image was subjected to five automated identification programs. These were chosen through a search for "plant id*" on the Android (via Google Play Store) and Apple (via App Store) platforms. The first ten free applications listed on both platforms on November, 2024, contained just three plant-specific applications.

Consequently, these turn into the study's main applications. They were as follows: Plantora, PlantNet (also known as Pl@ntNet), and PlantSnap. We also included Google Lens, a popular multipurpose generic image identification app that was freely available on the Apple and

Android platforms on November,5, 2024, and the natural history app iNaturalist , which can be used for photos of any taxonomic group, including plants.
In order to quantify descriptive statistics and, for PlantNet, the relationship between precise identification and app-reported recognition assurance (PlantNet was the only platform to offer this function using a numeric scale), baseline analysis was conducted for each application.
The accuracy of the subset of iNaturalist -processed photos that the program reported as meeting its internal confidence level for a confirmed (as opposed to possible) identification was also taken into account. Both PlantNet and LeafSnap enabled the structure in the supplied image to be classified as either a leaf, fruit, flower, or bark; bark was left out since no photographs fit into this category. To help with automatic identification, iNaturalist Seek enabled the precise spot of each image to be supplied as metadata. This could be done manually at the county level or by utilising geolocation information in the image. While it was possible to post more than one image of the same specimen using PlantNet and iNaturalist Seek, this feature wasn't utilised because every picture came from a different specimen. While it is acknowledged that the evaluation of congenericity may be impacted by the reinterpretation of plant species taxonomy, the taxonomic data utilised in this study adhered to Stace (2019). Additionally, we made sure that all applications' output was interpreted consistently, even when those programs differed internally (for example, Chamaenerion angustifolium, Chamerion angustifolium, and *Epilobium angustifolium* were treated as synonymous) in order to prevent bias.

Then, distinct generalised linear models (GLMs) were built for each of the five identification applications in order to comprehend the botanical and image elements affecting identification accuracy. An ordinal score derived from the focal application's identification performance was always the dependent variable: Five indicates that the application correctly identified the plant to the species level as its first option; four indicates that the second suggestion was correct; three indicates that the third suggestion was correct; two indicates that the fourth suggestion was correct; one indicates that the fifth suggestion was correct; and zero indicates that the first five suggestions did not contain the correct identification.

The following independent variables were input as fixed factors: flower presence (0/1), leaf presence (0/1), fruit presence (0/1), and plant type (woody, flowering herbs, grasses, sedges, and cryptogames). The previously mentioned picture quality metrics of exposure, focus, and saliency were input as independent variables as covariates. Every model has a cumulative logit link function and an ordinal distribution with a multinomial distribution. In each instance, Wiley Online Library, 25758314, 2023, 3 [11/12/2024], downloaded from https://besjournals.onlinelibrary.wiley.com/doi/10.1002/pan3.10460. For usage guidelines, refer to the Wiley Online Library's Terms & Conditions https://onlinelibrary.wiley.com/terms-and-conditions); the relevant Creative Commons License 932 | People and Nature HART et al. govern open access articles. Based on a comparison of delta Akaike's Information Criterion (ΔAIC) scores, this was found to be ideal (Akaike, 1973; Hu et al., 2011).

The scores for competing models are provided in the supplementary material. No competing models that used other statistically valid model distribution/function combinations were within ΔAIC of 10 of the optimal. Five more models were run, one for each application, with the dependent variable being whether the proper genus was provided (1) or not (0) as the top suggestion. All models employed a binary distribution with a log link function, and the independent variables were as previously mentioned. Variance inflation factors (VIFs) were computed for a blend of independent variables used in all models to make sure that the assumption of symmetry was satisfied and, consequently, that multiple linearity within each independent variable was low enough not to confuse the findings of species or genus accuracy. Variance inflation factors, or VIFs, were computed for each model's combination of independent variables. All of the VIFs were well below the (very liberal) top criterion score of 10 provided by Myers (1990) and Field (2000), with values ranging from 1.047 to 1.538.

RESULTS

Ecologists submitted a total of 857 plant photos for identification using Google Lens, iNaturalist Seek, PlantNet, Plantora, and flora incognita. All together, these photos covered 200 genera and 270 species. Images displayed cryptogames (n = 28), grasses (n = 50), woody species (n = 163), flowering herbs (n = 608), and sedges (n = 8). Overall, 26 photos had multiple organs (flower/leaf = 235; fruit/leaf = 16; flower/fruit = 3), while 600 photos displayed a single organ (flower = 297; leaf = 300; fruit = 3). In general, the images had strong saliency (1 to 3 positive scale: mean = 2.830 ± 0.265), were well-focused (1 to 3 positive scale: mean = 2.802 ± 0.307), and were appropriately exposed (-1 to $+1$ with 0 being optimal: mean = -0.008 ± 0.086 SD).

The first identification option was right for 69.8% of photos on average across all applications, and 85.5% of images had the right identification in the first five proposals. Nonetheless, Figure 1 shows that there was a significant difference in accuracy among the applications. When comparing the reliability of the top suggestion, the generic application Google Lens performed worse than the majority of the plant-specific applications combined (57% vs. 73%). The non-plant-specific naturalist tool iNaturalist Seek was in the middle of the pack at 66%. However, PlantNet, iNaturalist Seek, and Flora incognita all consistently performed (95%, 93%, and 92%, respectively) when it came to having the correct species in the first five options.
Plantora and Google Lens, on the other hand, performed significantly worse (74% and 71%, respectively). Nevertheless, 12 photos that none of the plant-specific apps had correctly identified were recognised by Google Lens. All five applications correctly identified 19.5% of the images as the first suggestion overall, and 96.3% of the images had the correct identification provided as the first suggestion by at least one of the five apps when the top three performing applications—PlantNet, iNaturalist, and flora incognita—were used in triplicate.

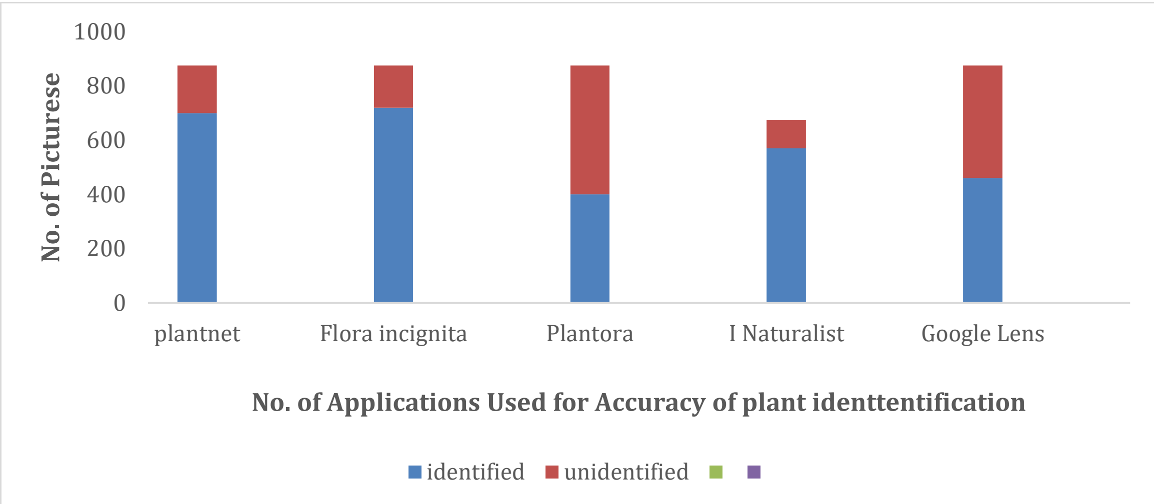


Fig.1 Identification of Accuracy of plant Identification App.

A binary classification of whether an individual should have trusted the identification (confirmed identification) or not (many possible identifications listed in order of likelihood) was offered by one application, iNaturalist . This was true in every instance for 560 out of 875 photos (66%) that had a confirmed identity. To put it another way, the subgroup of photos where the application-reported assurance threshold was reached had no false positives.
For each processed image, PlantNet offered a confidence score for each identification proposal. This was provided on a 0–5 scale to two decimal places at the time of the study; a more logical integer-based percentage has since taken its place, but the fundamental idea is still the same. A correctly recognised species had an average confidence score of 3.39 out of 5, whereas a mistakenly identified species had an average of 1.82 out of 5.

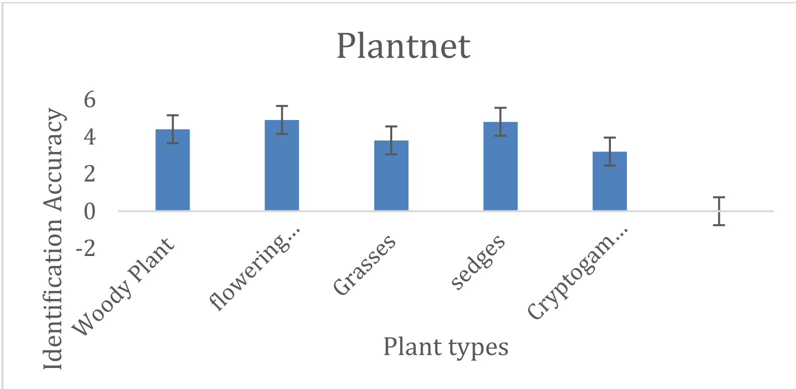
Nonetheless, Table 1 showed significant variations among plant species. Given the number of morphologically similar cryptogames species, the application was generally less confident of accurate identification, even when the detection was correct, for sedges and grasses than forbs and woody species; however, the confidence of correctly recognising for cryptogames was high.

Table: 1 shows the relationship between PlantNet's application-reported confidences on a 0–5 scale for successfully and erroneously identified species by plant type.

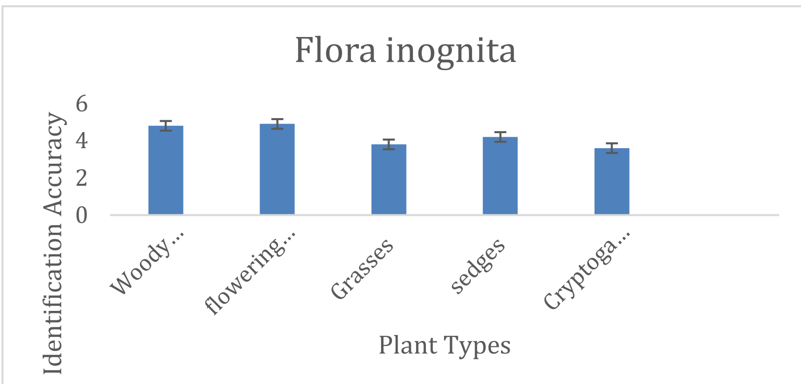
Plant Type	Self-assurance in the first suggestion when it is accurate		Confidence in the initial proposal, even though it is erroneous	
	Mean	SD	Mean	SD
Woody Plants	3.57	1.16	0.42	0.43
Flowering Herbs	3.85	1.05	0.62	0.56
Grasses	3.01	1.27	0.93	0.53
Sedges	2.41	1.75	0.36	0.02
Cryptogames	3.72	1.08	0.23	0.24

Overall, all five of the GLMs were significant (Table 2). Plant type significantly influenced identification success for each application, with the exception of iNaturalist, in a variety of ways. Figure 2 delves deeper into these trends. None of the botanical and image characteristics were significant for PlantNet and flora incognita, two highly effective plant-specific programs. On the other hand, the presence of a flower in the photograph greatly improved the effectiveness of the highly effective but more generic iNaturalist .

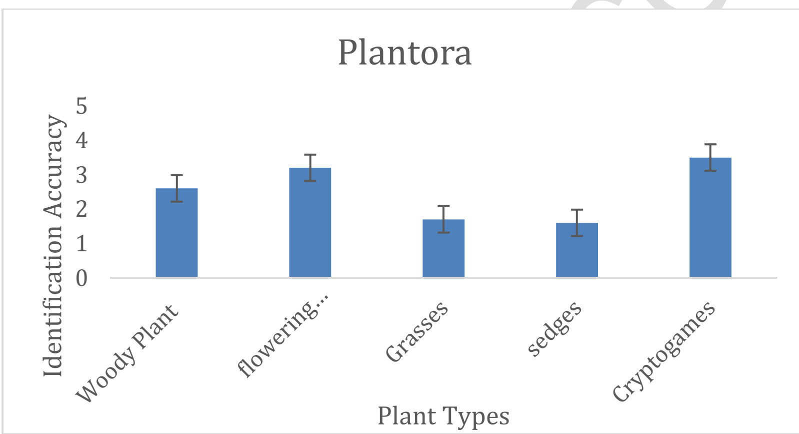
When a flower was present and the focal plant had high saliency—that is, when the focal plant's dominance and clarity in the image were good—the poor-performing apps, Plantora and Google Lens, performed noticeably better. With the exception of iNaturalist , plant type was a significant predictive variable in the GLM (Table 2). Plotting the estimated marginal means (EMMs) from the GLMs and conducting post-hoc testing allowed for a deeper investigation of any notable variations in identification accuracy in comparison to the application-specific EMM (Figure 2).


Plantnet
Identification Accuracy
6
4
2
0
-2
Woody Plant
flowering...
Grasses
sedges
Cryptogam...
Plant types

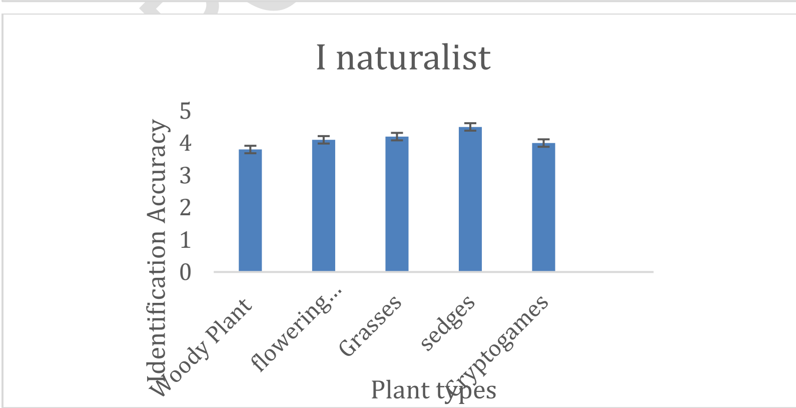
(a)

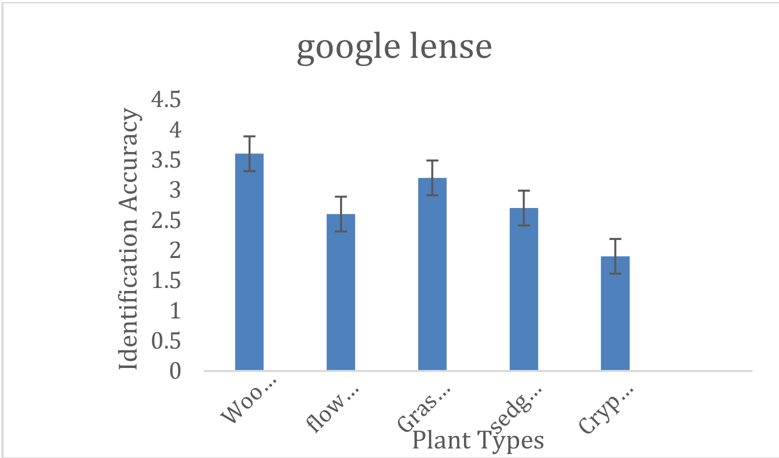

Flora inognita
Identification Accuracy
6
4
2
0
Woody...
flowering...
Grasses
sedges
Cryptoga...
Plant Types

(b)


Plantora
Identification Accuracy
5
4
3
2
1
0
Woody Plant
flowering...
Grasses
sedges
Cryptogames
Plant Types

(c)


I naturalist
Identification Accuracy
5
4
3
2
1
0
Woody Plant
flowering...
Grasses
sedges
Cryptogames
Plant types



(e)

Fig: 2 Estimated marginal means with standard error bars showing identification accuracy for plant type: (a) PlantNet; (b) Flora incognita; (c) Plantora; (d) iNaturalist and (e) Google Lens.

By using EMMs instead of raw data, it was possible to account for underlying variations in the presence or lack of organs or image quality metrics that differed with the kind of plant.
The mean accuracy in identifying for woody species was considerably greater than the mean for Google Lens, but it was comparable to the mean for each of the plant-specific applications.
On the other hand, forbs' identification accuracy on Google Lens was below the performance of those applications across all other plant types, while forbs' identification accuracy on the three other applications was not appreciably different from the overall accuracy found across all plant types for that application.
The issue was more complicated for the other kinds of plants. For the three plant-specific applications, the accuracy of grass identification was much lower than the mean; in other words, they did not perform well for grass identification. However, this was not the case for Google Lens, where the accuracy did not differ considerably for grasses. With the exception of Plantora, where accuracy for rushes and sedges was much lower than the overall average for Plantora, rushes and sedges were often identified with an accuracy that did not deviate from the mean identification accuracy for the application. With the exception of Plantora, which identified ferns and horsetails with accuracy that was identical to the mean, these plants were often identified with below-average accuracy. Overall, the lowest-scoring plant kinds on PlantNet and flora incognita still had higher identification accuracy.
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mean identification accuracy for the application. With the exception of Plantora, which identified ferns and horsetails with accuracy that was identical to the mean, these plants were often identified with below-average accuracy. Overall, the lowest-scoring plant types on PlantNet and Flora inconita still had higher identification accuracy than the highest-scoring plant types on Google Lens and Plantora. The identification accuracy of iNaturalist was close to the (high) mean in every instance, indicating that this application performs well for all common plant types. There were no discernible variations in accuracy between plant types. The following is the overall accuracy at the genus level (i.e., genus accurately identified as the highest suggestion): GoogleLens = 72.7%, Naturalist = 93.2%, PlantNet = 97.5%, Flora incognita = 95.8%, and Plantora = 21%.

TABLE 2: Generalised linear models of the variables influencing each application's species-level identification accuracy. In the first five recommendations, the dependent variable provided the location of accurate identification: 5 indicates that the first recommendation was right, 1 indicates that the fifth suggestion was right, and 0 indicates that the first five suggestions did not contain the correct identification. The models included a cumulative logit link function and a multinomial distribution; the test statistic for the entire model is the $\chi2$ likelihood ratio, and for the individual variables, it is $\chi2$ = Wald. P values that are significant are bolded. The direction of noteworthy outcomes is shown.

Characters	**Plant Net**		**Flower incognita**		**Plantora**		**i Naturalist**		**Google Lense**	
	X^2	*p*	X^2	*p*	X^2	*p*	X^2	*p*	X^2	*p*
Full Model	45.30	<0.002	45.25	<0.001	117.50	<0.001	94.5	<0.001	34.35	<0.001
Plant Type	26.90	<0.001	24.65	<0.001	29.14	<0.001	6.68	0.153	13.02	0.001
Flower Present	2.31	0.128	2.41	0.120	10.94	0.001	8.60	0.029	4.42	0.036
Leaf Present	0.35	0.546	0.37	0.537	1.21	0.270	0.81	0.363	0.25	0.625
Fruit Present	0.85	0.352	0.66	0.420	2.32	0.128	0.82	0.376	1.64	0.201
Exposure	1.45	0.226	3.61	0.057	0.33	0.568	1.89	0.170	1.60	0.203
Focus	0.071	0.798	0.68	0.413	3.02	0.103	0.63	0.431	0.78	0.375
Saliency	1.20	0.272	2.36	0.123	28.25	<0.001	0.53	0.552	7.25	0.069

DISCUSSION

The applications evaluated outperformed, or outperformed, earlier research (e.g. August et al., 2020; Jones, 2020; Pärtel et al., 2021) using 857 professionally identified photos of 270 species. As the initial recommendation, one or more programs accurately identified about seven out of ten photographs; when the three top-performing applications were combined, this number increased to over 9.7 out of 10. The right identification—or at least the right genus—often appeared among the top five options, even if it wasn't the initial one.

Two plant-specific applications outperformed the others for all plant types, however there were variations in identification performance between applications. The total accuracy of Flora incognita and PlantNet's first-choice identifications was 86.92% and 86.64%, respectively (see Bonnet et al. (2018) for the top machine learning algorithm's 73.32% accuracy). The relative performance of various plant types varied across all applications; flowering herbs and woody species generally performed better than grasses and cryptogames, where identification accuracy frequently depends on small-scale features like ligules and sporangia (Bonnet et al., 2018).

Two plant-specific apps outperformed the others for all plant kinds, however there were noticeable variations in identification performance between applications. Overall, Flora incognita and PlantNet obtained 86.92% and 86.64% accuracy on their first-choice identifications, respectively (see Bonnet et al. (2018) for the top machine learning approach, which had an accuracy of 73.32%). In all applications, the relative performance of various plant types varied; forbs and woody species generally performed better than grasses and cryptogames, where identification accuracy frequently depends on small-scale features like ligules and sporangia (Bonnet et al., 2018).

Our findings unequivocally demonstrate that these free mobile phone applications have an identification accuracy high enough to be very helpful in applied ecological contexts for species-level identifications. Apps must be reliable if users are to trust the identifications they supply. iNaturalist stood out in this respect. If the app's confidence threshold is surpassed, an identity is "confirmed." Out of 875 photos, 561 (66%) had a confirmed identification, meaning there were never any false positives and the identification was always accurate. As a result, even though the app's overall recognition accuracy was marginally lower than that of other applications, its confidence was well-founded. In numerous professional situations, it would be preferable to have this degree of certainty in species identification rather than less certain identifications. We are not arguing that automated identification software is yet ready to take the place of experienced botanists' field knowledge or conventional identification techniques. But as other writers have pointed out (e.g. Bonnet et al., 2018), High-quality ecological data can already be produced by these applications, and there being helpful in assisting with ecological monitoring and surveying tasks. Applications have the potential to support a larger user base due to their intuitive and accessible nature (Joly et al., 2014; Jones, 2020), particularly when compared to conventional identification keys (Rehorek & Shotwell, 2018). This could be especially useful for citizen science projects, trainee ecologists in early-career positions, or educational contexts. It should be mentioned that most evaluations, including this one, may exaggerate the overall application performance because the evaluated photos will, barring a particular selection to the contrary, tend to display species that are somewhat common and perhaps well-represented in the photos that these programs use to learn. However, in our study, no image pre-processing was done to optimise the record photos before sending them to each application, which may have decreased the recognition accuracy of some images. This lack of image optimization may have affected some applications more than others, as anecdotal data suggests that Google Lens works better when photos are cropped to highlight important plant features in more detail.

In the end, identification accuracy depends on the learning chances available to the applications, which are influenced by the quantity of photographs provided. This probably accounts for at least a portion of the variations in accuracy among various plant species. For instance, forbs with eye-catching blossoms receive more uploads than grasses, and those characteristics that draw more user attention are also probably simpler to spot in photos. Location is another element that restricts uploaded photos and, consequently, their accuracy. This study concentrated on the UK, where there are probably a lot more people uploading photos than in less developed, sparsely populated, or more isolated areas.

It takes either a highly comprehensive key (e.g. Stace, 2019) or several field guides that cover not just trees, shrubs, and wildflowers but also plant kinds that are usually left out of general volumes, like grasses, sedges, and rushes, to identify the plant species found at the majority of field sites. Despite this, it may still exclude non-native species and garden escapes, which can potentially cause issues for automated identification (August et al., 2020). Though it doesn't always save time in identification, carrying guidelines on mobile devices as PDFs reduces the weight and annoyance that paper copies impose. Professionals could employ automated programs to recommend identifications for specimens outside of their area of knowledge or to support identifications, similar to obtaining a second opinion. Applications might possibly save a significant amount of time by following up on these initial identifications utilising particular taxonomic keys and additional resources. For professional users, applications and conventional techniques can complement one another.

Although they have certain limitations, applications offer a great starting place for novice or non-professional users to learn more about plants. Applications that offer a tentative identification can help inexperienced users identify plants either directly (when the identification is accurate) or indirectly (by directing users to the appropriate place in a field guide to investigate related species). This is crucial since unskilled users could find it difficult to know where to begin and might even lose interest without the application's direction. Similarly, field guides' taxonomic organisation and explanations of the essential taxonomic and identification characteristics that support a species' designation offer users the opportunity to learn and become more confident, which may increase user engagement.

Similar to professional users, the two identification approaches' complementarity can offer advantages that neither one alone could. When it comes to determining the adoption of automated identification applications, the user experience and how users interact with the applications in real-world situations are probably just as crucial as the applications' actual recognition accuracy. Information about whether and how the professional community uses this technology, as well as how ecological practitioners perceive these digital tools, is currently lacking. Additionally, nothing is known about how non-professionals utilise identification apps.

We conclude that accurate identifications to a satisfactory taxonomic level are already provided by free mobile phone automated programs. With more reference photos, better algorithms, and superior machine learning, application identification accuracy will increase over time (Bonnet et al., 2018; Kaur & Kaur, 2019). The range of taxonomic groups that can be effectively identified using automated applications will also increase if there is a desire to provide these automated identification devices ever more appealing to all users, even though for some species the requirement for microscopic examination may prove to be an insurmountable barrier.

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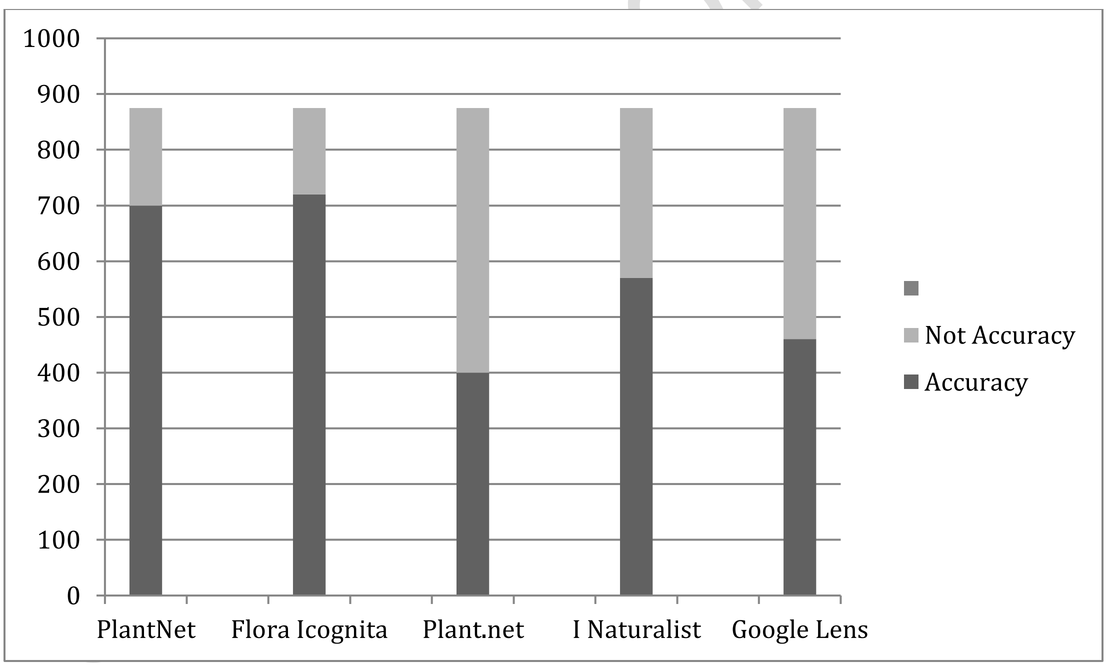

Figure 1 Identification of Accuracy of Plant Identification Applications