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Preserving traditional plant knowledge via AI-driven identification and human-centered mobile design

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Abstract

The loss of indigenous botanical knowledge poses risks to biodiversity conservation and community health by weakening the knowledge of medicinal plants and their traditional use as local plant-based health care options. An integrated system that combines deep learning image recognition with a user-friendly mobile interface to document and preserve medicinal plant knowledge is presented in this study. A Convolutional neural network (CNN) was trained on a curated dataset of fourteen Nigerian medicinal plants, achieving 78.9% validation accuracy in species identification. Recognized plants are linked to an expert-curated knowledge base (with features, compounds, and uses) structured as a graph for efficient retrieval. A mobile app prototype was also designed with intuitive user interfaces, such as a landing page for navigation and an image-based search screen for plant identification. The Human-Computer Interaction (HCI)-driven design emphasizes ease-of-use, with clear labels and minimal steps, enabling users (including elders and youth) to capture plant images and instantly access scientific and local names, medicinal properties, and usage guidelines. In "active learning" mode, low-confidence predictions trigger the retrieval of similar examples to guide users. This Artificial Intelligence plus Human-Computer Interaction approach addresses issues of manual identification (subjectivity, expertise gap) by automating recognition and by empowering communities to digitally record ethnobotanical knowledge. By improving accessibility to reliable plant data, this system contributes to Sustainable Development Goals (SDG) 3 and 15.

Keywords: Human-Centered Mobile Design, Medicinal Plant, Mobile App Plant Prototype, Traditional Plant Knowledge

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Introduction

Medicinal plants are key players in the field of medicine as well as an important part of cultural heritage. However, the knowledge associated with medicinal plants, particularly the names of medicinal plants and their ethnobotanical applications, is declining very fast, especially among young people (Chitakunye et al., 2023). Factors leading to this problem range from language change, urbanization to a lack of digital documentation. The loss of traditional knowledge in this case can be traced in areas like Nigeria where native language and ways of life are declining (Chitakunye et al., 2023). Furthermore, insufficient digital infrastructure (such as inadequate Internet connectivity and availability of mobile devices) poses additional barriers to the exchange of knowledge within remote communities (Chitakunye et al., 2023). In the absence of any corrective action, there is an increased possibility of loss of knowledge of medicinal plants.

The emergence of recent developments in AI provides us with opportunities that can be leveraged in plant conservation as well as healthcare. For instance, techniques such as machine learning and deep learning have shown tremendous progress in solving image processing problems through the use of convolutional neural networks (CNN) (Obanewa & Olope, 2024). In botany, Artificial Intelligence (AI) has enabled plants to be identified based on their leaf or flower images, and this has reduced the amount of effort and labor needed (Wäldchen et al., 2018). But accurate identification is not just a matter of taxonomics; it is also the basis of plant material that is used to authenticate that plant material, as many important medicinal plants have morphologically similar look-alikes that are easily misidentified or even substituted, which is dangerous to both the research and the people’s safety (Abdollahi, 2022; Bhutada et al., 2023; Kaur & Singh, 2021).

This authentication step is also essential for standardization; the plant material used in plant studies or in herbal product production should be the same in terms of species identity and in the expected phytochemical profile. Building on this foundation, AI-based systems could further analyze the bioactivity of phytochemicals, classify plants at more precise taxonomic scales, and discover drugs from plant-based compounds by linking the information that is verified and standardized to predictive models of bioactivity (Ydyrys et al., 2025). Significantly, convolutional neural networks that learn from big botany image data facilitate photo-based recognition of plants using smartphones for non-expert users (such as farmers, health professionals, and citizens) in the wild (Liu, 2025; Paulson & Ravishankar, 2020). Simultaneously, Human-Computer Interaction (HCI) research has acknowledged the significance of user-centered design in terms of the technology adoption process in a cultural context (Winschiers-Theophilus & Bidwell, 2013). Mobile applications and other digital tools co-designed by the community can help them document their knowledge and disseminate it in compliance with the traditional norms (Chitakunye et al., 2023; Loh et al., 2024). According to the previous studies, the proper design of mobile applications will help the community collect, arrange, validate, and ensure that its knowledge remains long-lasting and reliable (Bawingan et al., 2024; Beebwa et al., 2019; Chitakunye et al., 2023; Mat Yusoff et al., 2023). For example, mobile ethnographic applications have been recommended as a way of ensuring the protection of indigenous knowledge, combining local wisdom with technology (Bhanye et al., 2024; Chitakunye et al., 2023).

Taking into account the above trends, we design a new AI-HCI technology with a knowledge graph that seeks to preserve information regarding medicinal plants. Specifically, the CNN algorithm was trained using data from Plant Village. But for this purpose, fourteen types of classes that exist in Nigeria were considered. Additionally, a prototype was developed to incorporate this algorithm in a user-friendly mobile application. Apart from identifying the plants through scientific names and local names, the system is capable of providing medicinal characteristics of those plants from the knowledge database. Simple and effective user interfaces have been developed to facilitate the utilization of the technology by people with lower technical skills. This study combines a deep learning algorithm with mobile prototypes to make the digitization of plant knowledge feasible.

Methodology

Conceptual framework

The proposed system consists of three main modules, namely, the deep learning-based model for plant classification, a knowledge base related to species identification, and finally a mobile application front end. The system development process is outlined as follows.

Dataset and preprocessing

A collection of images of 14 plant species of medicinal value that can be found in Nigeria, including herbs such as *Azadirachta indica* (Neem), *Murraya koenigii* (Curry leaves), *Psidium guajava* (Guava), among others, was used for the research. The total number of images available in the Plant Village dataset on Kaggle was 829, with 668 used for training and 161 for validating the dataset. The statistics for the images used are shown in Table 1. Every image was resized to a resolution of 224x224 pixels and normalized. An 80% training, 10% validation, and 10% independent testing split was employed using Kera's ImageDataGenerator, making sure that all classes were fairly represented in both datasets. Since there was a limited dataset, data augmentation techniques, such as flipping and rotation, were used during training to aid in better generalization (MacIsaac et al., 2024).

Table 1: Dataset Statistics

Serial Number	Name of Leaf	Total
1	*Azadirachta indica* (Neem)	60
2	*Citrus limon* (Lemon)	57
3	*Hibiscus rosa-sinensis*	43
4	*Jasminum* (Jasmine)	71
5	*Brassica juncea* (Indian Mustard)	34
6	*Artocarpus heterophyllus* (Jackfruit)	56
7	*Mangifera indica* (Mango)	62
8	*Mentha* (Mint)	97
9	*Moringa oleifera* (Drumstick)	77
10	*Murraya koenigii* (Curry)	60
11	*Ocimum tenuiflorum* (Tulsi)	52
12	*Psidium guajava* (Guava)	65

Serial Number	Name of Leaf	Total
13	*Syzygium cumini* (Jamun)	39
14	*Syzygium jambos* (Rose Apple)	56

CNN architecture and training

A custom CNN architecture was used in the study, which was constructed with the help of TensorFlow/Keras library. This architecture includes three Conv2D layers, with 32, 64, and 128 filters correspondingly and kernel sizes of 3×3 as well as ReLU activation functions (Ghosh et al., 2022). The flattened output from the convolutional layer then moves to a dense layer having 128 units with ReLU activation function. A dropout rate of 30% was used for the purpose of preventing the model from being overfitted. Finally, the softmax classification layer with 14 outputs was used to classify each plant based on its respective category (Maheshwari et al., 2025).

Knowledge base construction

At the same time, a knowledge database of the therapeutic applications of each of the plants was developed (Larmande & Todorov, 2021). For every species, experts compiled information on their main leaf characteristics (such as leaf shape and color), chemical compounds, and their effects on human health. All of that information was then placed in a table form. The information was programmatically extracted and used to build a knowledge graph in an undirected form using NetworkX: the plants themselves are nodes connected with feature, compound, and effect nodes. The generated graph consists of 168 nodes and 186 edges (14 nodes representing plants plus additional nodes connected to each plant). The above-mentioned semantic structure provides the possibility to carry out flexible queries: for instance, a user can follow a link from a benefit (node) to all plants providing it and vice versa.

Embedding index and similarity retrieval

In order to enhance the support and the user's active involvement in the process, 128-dimensional embeddings have been created using a trained CNN (the second last layer). This vector was normalized, and an index using FAISS (inner-product similarity) was created. For a new image at run time, the CNN was run in order to obtain the class probabilities and the vector. If the confidence value for the top probability is below the threshold value (60%), then uncertainty arises. Under such situations, the Facebook AI Similarity Search (FAISS) index was used to find the top-K most similar images using cosine similarity. These images (along with their real classification) are then shown to the user in the form of “examples like these”. In all other cases (i.e., if confidence is high enough), predicted classification is returned. In this way, when a prediction is not confident, the system falls back to the nearest neighbor approach.

Mobile interface design

The interface prototype was built with Figma. The design approach employed centered around the needs of the end-user. An iterative wireframing process based on feedback from university students was performed.

Evaluation procedures

In this case, attention was on the aspect of designing the system and proving its technical capabilities. In order to provide an unbiased assessment of the CNN model, we divided the dataset into three different subsets: 80% training, 10% validation and 10% independent testing. We used stratification to keep the 14 plant species in the three subsets. We used the training subset to train our model and use the validation images to check our model performance as we train and develop our model. The independent test images is not used for training or model selection and is evaluated only after our final model has been selected. Model performance was assessed with accuracy, precision, recall and F1-score (Richter & Kim, 2025). Since the task involved 14 plant species, we reported both macro-averaged and weighted-averaged precision, recall and F1-score. Macro-averaging assesses each plant class equally and weighted averaging takes into account the number of samples per plant class. We also generated a confusion matrix to explore class-specific patterns of prediction and find plant classes that were more frequently confused with one another. The final performance metrics reported in the results section were based only on the independent held-out test set. Thus, the results of the test show the model's performance on images that were not used for training or validation of the model. In the prototype phase, a testing method was used involving 8 targeted users (university students), 3 elders in the university community, and 1 herbalist to test whether the UI flows were clear. As a result of such tests, the navigation was made simpler. The formal field study is left for the future.

Results

As shown in Figure 1, the learning patterns in training and validation accuracy are very stable over the next 10 epochs with a value of around 0.77 and 0.81 respectively and no evidence of overfitting or underfitting, but validation accuracy is higher than training accuracy which typically corresponds to regularization or variation in data partition.

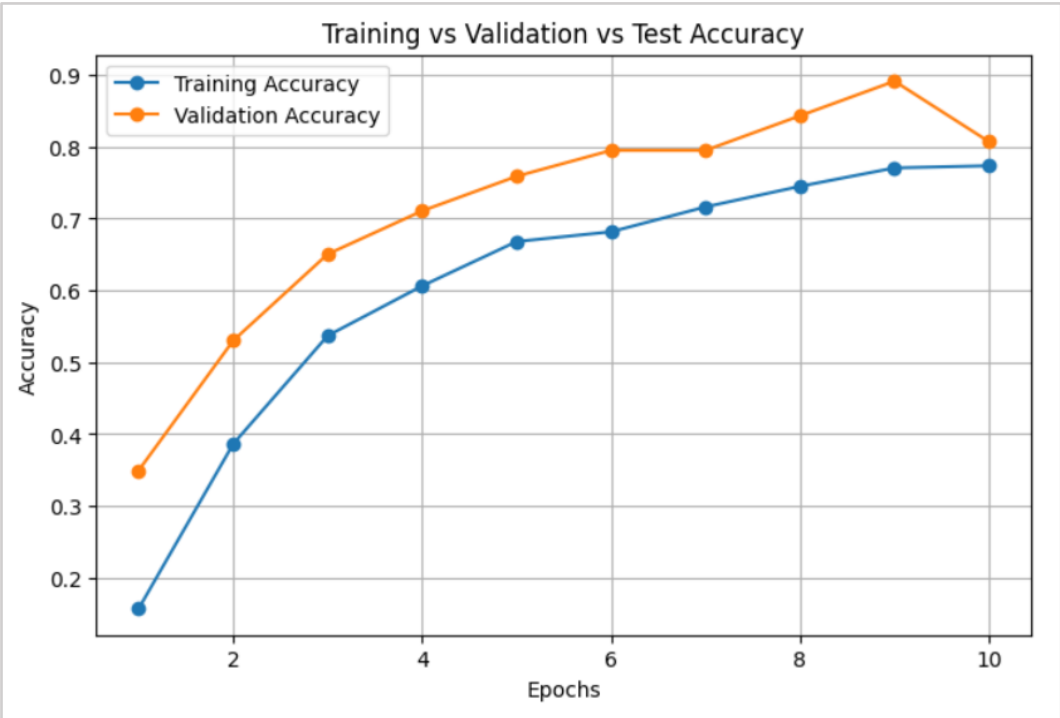

Figure 1. Model Performance

The confusion matrix in Figure 2 also shows very good classification in all 14 species with perfect accuracy for the class Mentha (Mint) and *Syzygium jambos* (Rose Apple) (10 correct instances), but there are a few false positive classifications between species (for example, *Syzygium cumini* (Jamun) and *Ocimum tenuiflorum* (Tulsi)), which may be due to fine-grained visual features or because all species are different. In quantitative terms, as shown in Table 2, the model shows a very good global performance with a test loss of 0.4072 and test accuracy of 83.13% (0.831325) with macro precision of 0.8647 and macro recall of 0.8053 and macro F1-score of 0.8019 (with weighted performance scores of 0.8679 precision, 0.8313 recall and 0.8179 F1-score). The high precision and the low recall mean that the model cannot overfit or underfit but is still good in class classification and thus is a good model to learn multiple species of plants.

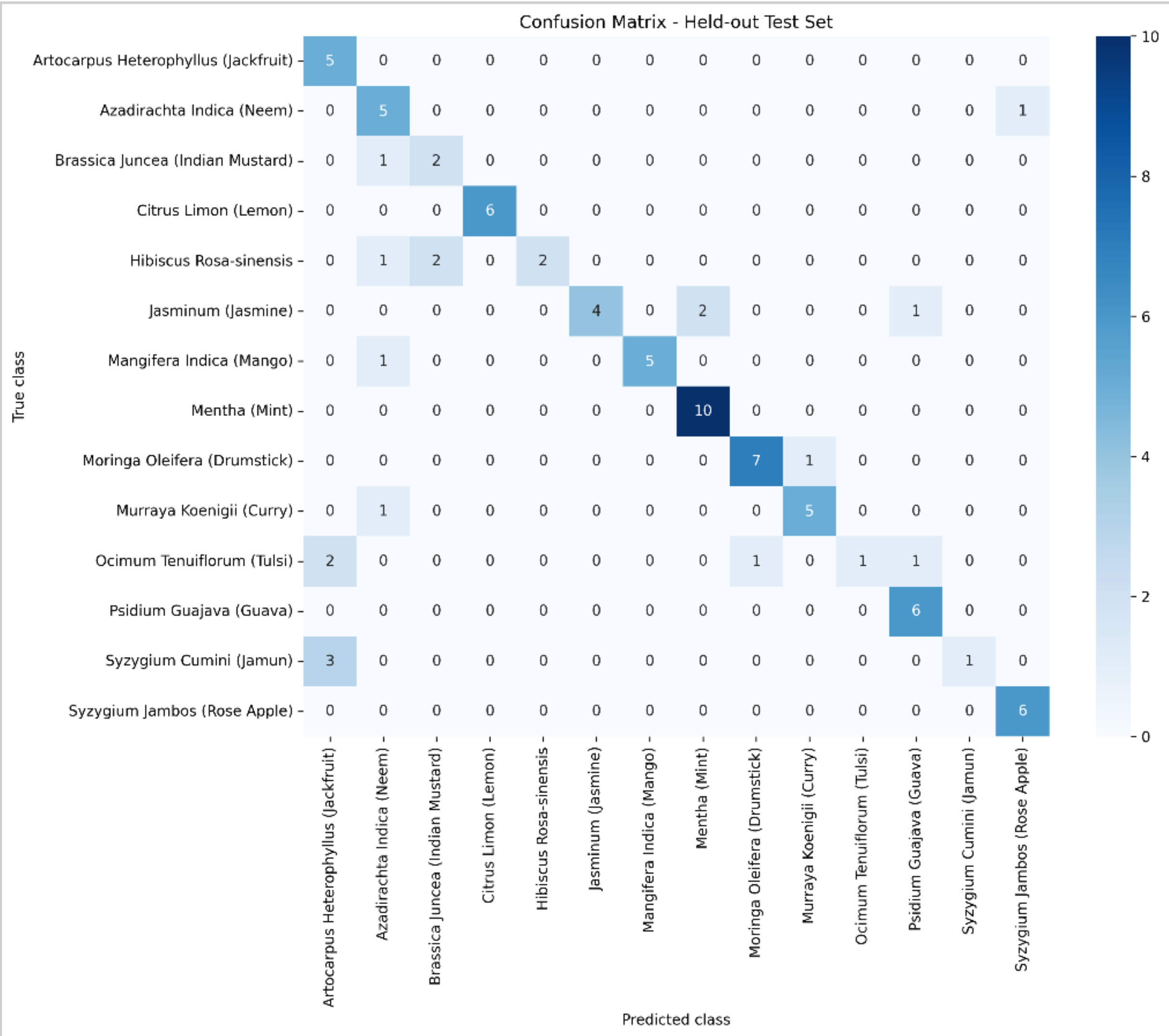

Figure 2. Confusion Matrix

Table 2: Performance Metrics Scores

	Metric	Value
0	Test loss	0.407248
1	Test accuracy	0.831325
2	Macro precision	0.864711
3	Macro recall	0.805272
4	Macro F1- score	0.801901

5	Weighted precision	0.867886
6	Weighted recall	0.831325
7	Weighted F1- score	0.817893

A qualitative example of the identification pipeline on some sample images is shown in Figure 3. In cases where the images were from *Artocarpus heterophyllus* (Jackfruit), the plant species was correctly predicted with a probability of 1.0. In the same way, the model correctly identified *Azadirachta indica* (Neem) with a confidence score of 1.0 in one of the samples under examination. However, there was one sample of Neem that had been erroneously identified as *Citrus limon* (Lemon) with a confidence score of 0.549. This implies that even though the classification power of the model was very high, there were instances of misidentification.

```
--------------------------------
IMAGE: /kaggle/input/datasets/peacefalola/14medicinal-plant/14 Medicinal Plant Dataset/Artocarpus Heteroph
yllus (Jackfruit)/AH-S-010.jpg
TRUE: Artocarpus Heterophyllus (Jackfruit)
PREDICTED: Artocarpus Heterophyllus (Jackfruit)
CONFIDENCE: 1.0

--------------------------------
IMAGE: /kaggle/input/datasets/peacefalola/14medicinal-plant/14 Medicinal Plant Dataset/Artocarpus Heteroph
yllus (Jackfruit)/AH-S-011.jpg
TRUE: Artocarpus Heterophyllus (Jackfruit)
PREDICTED: Artocarpus Heterophyllus (Jackfruit)
CONFIDENCE: 1.0

--------------------------------
IMAGE: /kaggle/input/datasets/peacefalola/14medicinal-plant/14 Medicinal Plant Dataset/Azadirachta Indica
(Neem)/AI-S-004.jpg
TRUE: Azadirachta Indica (Neem)
PREDICTED: Azadirachta Indica (Neem)
CONFIDENCE: 1.0

--------------------------------
IMAGE: /kaggle/input/datasets/peacefalola/14medicinal-plant/14 Medicinal Plant Dataset/Azadirachta Indica
(Neem)/AI-S-005.jpg
TRUE: Azadirachta Indica (Neem)
PREDICTED: Citrus Limon (Lemon)
CONFIDENCE: 0.549
```

Figure 3. Sample Predictions

The prototype does support some browsing functionality, which becomes available after plant recognition in the form of linear browsing. Figure 4 shows the result of a predicted plant by the model with its key leaf features, active compounds, and medicinal benefits.

The design of the prototype was carried out to offer an easy interaction process to the user when trying to find and store information on medicinal plants. Figure 5(a) shows the splash screen of the application, which introduces the application to the user through its brand identity. Figure 5(b) shows the onboarding screen, which was meant to offer users an introduction to some of the features offered in the application, such as plant identification, the information available regarding certain plant species, and so forth. Figures 5(c) and 5(d) illustrate, respectively, the sign up and login pages for the application, whereby one can create an account as well as log in to the account.

```
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TOP PREDICTIONS:

Artocarpus Heterophyllus (Jackfruit) -> 1.0
Syzygium Cumini (Jamun) -> 0.0
Psidium Guajava (Guava) -> 0.0
Syzygium Jambos (Rose Apple) -> 0.0
Murraya Koenigii (Curry) -> 0.0

SIMILAR IMAGES:
Artocarpus Heterophyllus (Jackfruit)
Artocarpus Heterophyllus (Jackfruit)
Artocarpus Heterophyllus (Jackfruit)

PREDICTED: Artocarpus Heterophyllus (Jackfruit)
CONFIDENCE: 1.0
SIMILARITY CLASS: Artocarpus Heterophyllus (Jackfruit)

================================
🌿 IDENTIFIED PLANT: Artocarpus Heterophyllus (Jackfruit)

🔍 KEY LEAF FEATURES:
- Elliptic to obovate leaves; leathery texture; shiny upper surface

🧪 ACTIVE COMPOUNDS:
- Artocarpin
- flavonoids
- saponins
- tannins

💊 MEDICINAL BENEFITS:
- It helps manage blood sugar levels
- fights microbial infections
- promotes wound healing
- and supports immune function.
```

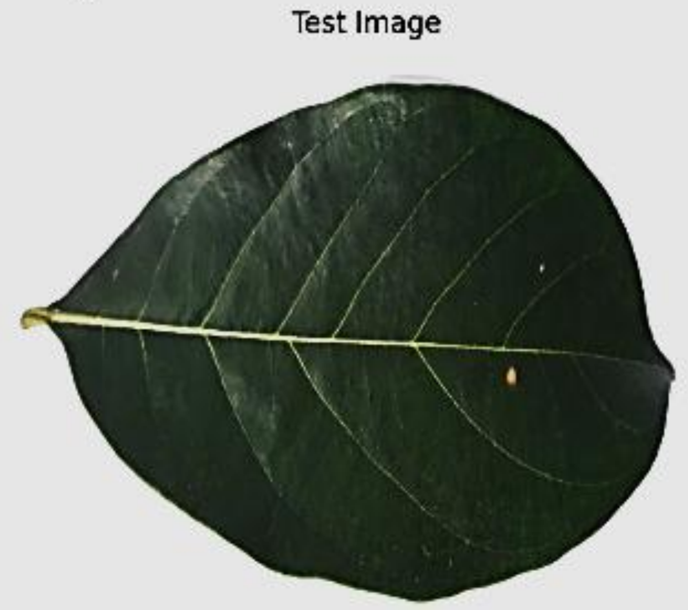

Figure 4. Plant Information

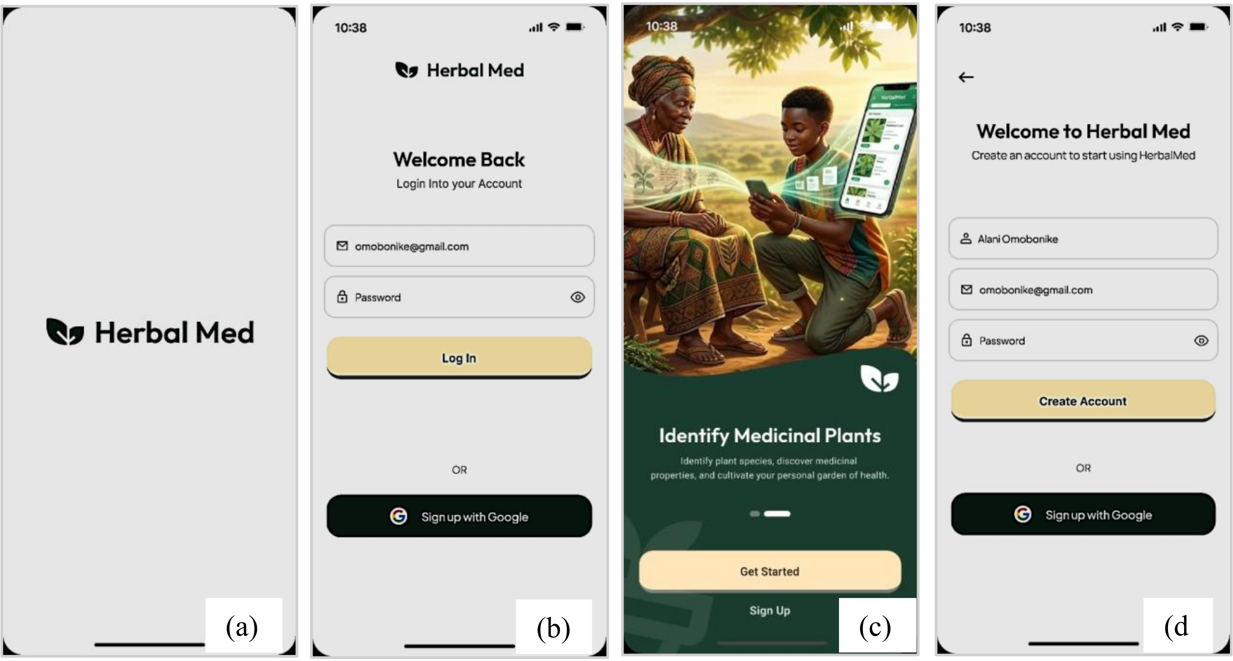

Figure 5. (a) Splash screen, (b) Onboarding screen, (c)- Sign up screen, and (d) Login screen

Figure 6 shows some of the interface capabilities that were built into the application design. Figure 6 (a) is the homepage with the search bar and the scanning capability, among others, with recommendation of certain types of medicinal plants. Figure 6(b) is the search results page where the medicinal plants have been identified from the user searches or uploaded pictures. Plant detail in Figure 6 (c) depicts the information regarding plant details such as medicinal usage, botanical data and its benefits. Figure 6(d) is an example of a contribution page where users and traditional knowledge providers can contribute their medicinal plant information.

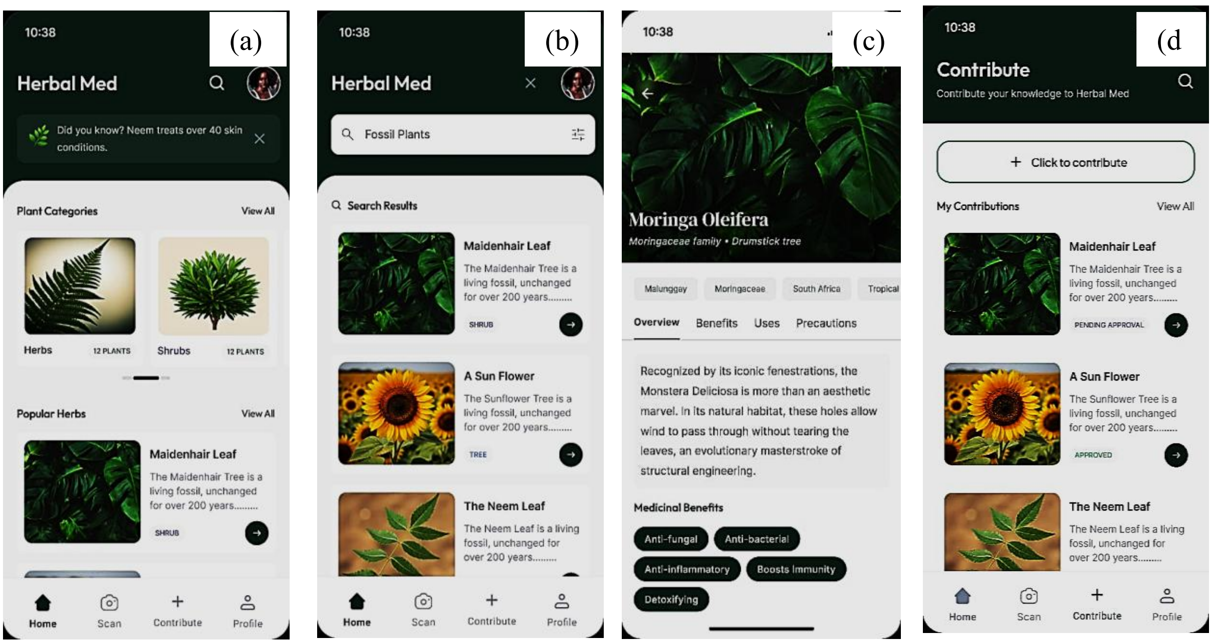

Figure 6. (a) Home page, (b) Search results, (c) Plant details page, and (d) Contribution page

Figure 7 depicts the AI-powered interactive functionalities provided by the application. Figure 7(a) is the contribution page where users can fill in their contributions on plant names, medicinal uses, and images. Figure 7(b) shows the scan page that provides the user with an option to scan the images or leaves of plants through the camera of the device. Figure 7(c) is the page that gives an output after processing the plant images through the deep learning model, which displays the result of plant class, its confidence level, and medicinal information accordingly. These interfaces integrate the principles of Artificial Intelligence and Human-Computer Interaction into one platform for identification and accessibility of medicinal plants.

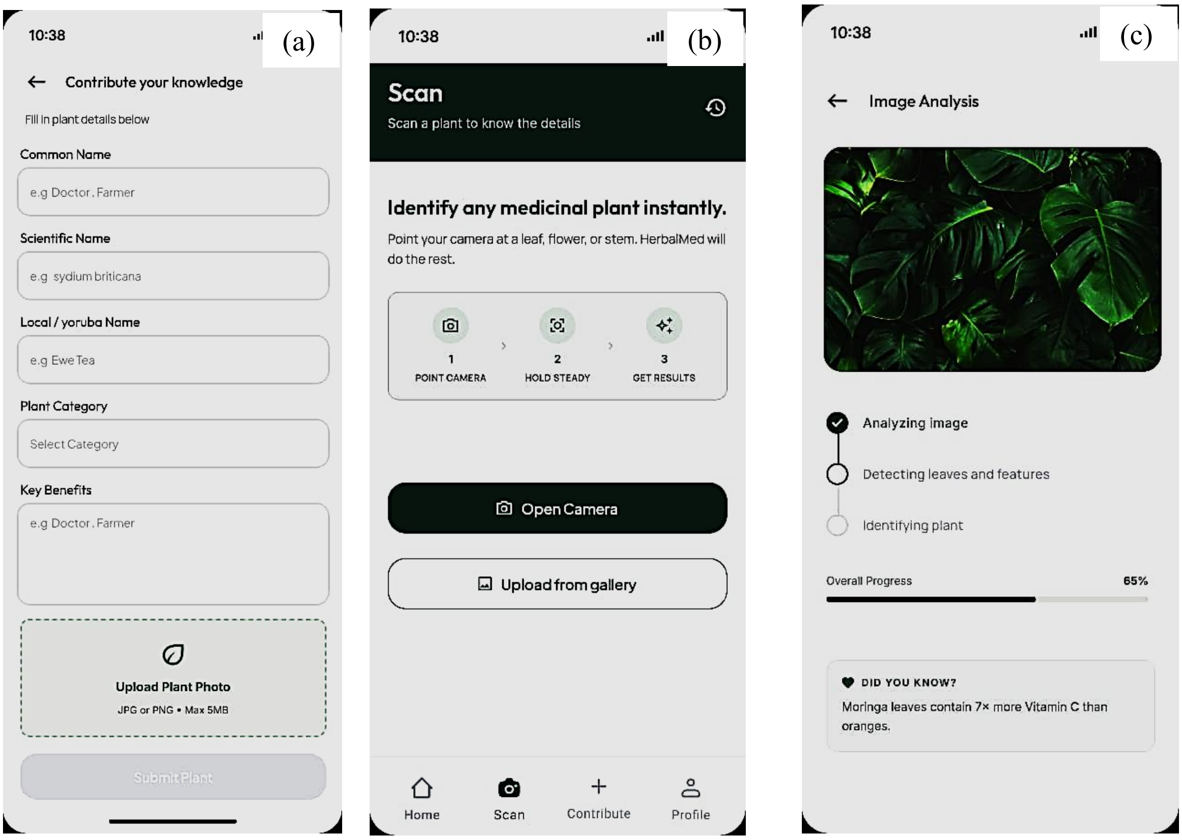

Figure 6. (a) Contribution form page, (b) Scan page, and (c) Plant analysis page

Discussion

Based on the observed increase in accuracy in training (Figure 1), it can be noted that the CNN managed to capture important visual features related to medicinal plants. The increasing trend in accuracy through various epochs confirms that the employed preprocessing and augmentation methods were effective in improving feature learning and optimization. The trend in validation accuracy shows that the generalization capacity of the model to new data is adequate. Overfitting is indicated by the difference between training and validation accuracies after several epochs. Such an occurrence is typical in deep learning models, whereby the model starts to memorize instead of generalizing on training samples as training proceeds. However, it is notable that validation accuracies held quite well even during such occurrences, suggesting that the model maintained some predictive power despite some signs of overfitting.

From the Figures showing the results from the prediction outputs, it can be observed that the proposed neural net model was able to recognize certain species of plants accurately based on very high confidence levels. It is interesting to note that the recognition of samples from Jackfruit and Neem plants had a confidence level of 1.0. From high prediction values, it can be inferred that the model was able to capture all features present in the leaves. The prediction of Neem as Lemon, however, shows how the model has some weaknesses as well. The low prediction value of 0.549 suggests some degree of uncertainty in the prediction process, which could be caused by some factors. This could be due to the similarity of the appearance of some of the leaves, environmental factors, or simply a lack of representative samples for certain categories.

The results obtained by the experiment indicate that artificial intelligence is capable of playing a crucial role in the digital preservation of knowledge of medicinal plants. The use of the above-mentioned system allows identifying medicinal plants without reliance on the exclusive expertise of specialists. Moreover, the use of HCI principles in conjunction with AI further reinforces the notion of preservation as well. In the context of AI and HCI, knowledge preservation may be participative, whereby communities can get involved in the process of documenting and disseminating data on medicinal plants. Therefore, this system helps not only with studying plant classification but also in relation to other purposes of biodiversity preservation and cultural heritage.

Nevertheless, there are several issues that should be taken into account. The current model might cause an error in identifying the species that look similar to each other, and this can be dangerous if the plant is poisonous. In order to address this problem, the proposed prototype would give warning messages when there is uncertainty in identifying a particular plant and recommend checking other sources. The system would also include a "poison" or toxicity check database that would warn the users whether the plant that was mistakenly identified is one of those with poisonous lookalikes. In addition, the current list of plants (14 species) represents just a small portion of the plants in Nigeria.

For HCI, although initial feedback was positive, formal user studies involving elderly and young people would need to be conducted to measure trust and learnability. In terms of task completion and error rates, these can only be measured in future studies using HCI research on citizen science applications. This research fits into the larger sustainable development goals. Digitization of botanical data not only helps with meeting SDG 15 (Life on Land), which is about preserving biodiversity, but also SDG 3 (Good Health and Well-Being). Through that lens, this AI-HCI system represents an approach to biodiversity conservation with the involvement of local communities.

Conclusions

A combined effort to use deep learning along with human-centered design for conservation of plant-based medicines was illustrated. The CNN model used in this study has the ability to recognize plants based on photographs, and this information can be delivered through a user-friendly mobile application (model). With the help of knowledge graph, it is possible to materialize abstract concepts such as herbal lore. To address the problem of poor HCI practices, large icons were used in the application interface design process. According to initial results, this combination of AI and HCI can help in both education and conservation, as users will be able to identify various plants and learn more about their benefits at once.

Future work will focus on broadening the scope and evaluating real-world impact. The number of images from different species at different times of the year will increase, making the model more robust. The graph database will be expanded to include cultivation data Graph Neural Network (GNN) for missing-link prediction in detecting feature–compound–benefit associations will be explored as well as the integration of GNN embeddings with CNN image embeddings for classification. These extensions will build on the current CNN-based classification and FAISS-based similarity retrieval as well as the knowledge graph and GNN as active parts of our system. Also, it is imperative to undertake a study involving more herbalists and community people to evaluate the user-friendliness of the application as well as its ability to document participatory knowledge in such processes. Participatory designs involving indigenous communities will make sure that the tool is fit to use by the knowledge holders. In conclusion, by applying AI to recognize plant images and HCI to design an inclusive tool, this innovative technology provides a strong answer to the issue of erosion of knowledge regarding medicinal plants. This project highlights the way modern technology can be combined with traditional knowledge, ensuring the survival of the vital information for future generations.

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Conflict of interest statement

The authors declare no conflict of interest.

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