DEVELOPMENT OF CITIZEN SCIENCE MOBILE APP FOR BIODIVERSITY INVENTORY WITH GOOGLE VISION AI

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Abstract *This research presents the development of a mobile application for biodiversity inventory using a citizen science approach. The app, named BioMap, is designed to support biodiversity documentation and conservation through active public participation. It features automated identification of biodiversity elements and image-based geolocation extraction and mapping. The primary objective is to address critical challenges in biodiversity data collection through crowdsourcing, particularly the issues of inaccurate geotagging and species misidentification found in existing citizen science platforms. BioMap not only leverages citizen science to improve the accuracy of biodiversity inventories but also addresses the limited availability of public-involved validation methods. The app is developed using Flutter, primarily for Android devices, and integrates real-time data synchronization via Firebase Firestore. It also includes an interactive map powered by the Google Maps API and a dual-validation flagging system, allowing users to mark uploaded data as either correct or incorrect to inform others about its reliability. Field testing conducted at Hutan Simpan Kekal Panti demonstrated the effectiveness of the application across all core functionalities. Notably, all uploaded records (n=10) were accurately georeferenced and mapped, indicating a high level of spatial precision and usability based on user-reported outcomes.*

Keywords: *mobile apps, GIS, automated mapping, citizen science, biodiversity*

Introduction

Citizen science broadly refers to the active involvement of the public in generating scientific knowledge, often through collaborative data collection and analysis (Bonney et al., 2014; Vohland et al., 2021). Over the past two decades, advances in digital technologies have transformed citizen science by enabling wider participation through mobile applications, online platforms, and low-cost sensors (Haklay et al., 2021). These tools not only enhance data accessibility but also allow volunteers to contribute meaningfully to ecological monitoring and conservation initiatives (Hecker et al., 2018). In biodiversity research, citizen science has become a valuable approach for documenting species distributions and ecosystem changes, complementing professional surveys with large-scale, distributed observations (Theobald et al., 2015).

Biodiversity inventories, which record the occurrence of flora and fauna in a specific area, are a cornerstone of ecological monitoring and conservation planning. Such inventories can range from small-scale assessments—such as counting tree species in a school yard—to comprehensive databases of organisms within protected areas (Association of Fish & Wildlife Agencies, 2018). These data are crucial for identifying conservation priorities, such as Key Biodiversity Areas (KBAs), and for tracking ecological change over time (Stephenson, 2020). However, traditional inventory methods are often time-consuming and resource-intensive, highlighting the need for digital tools that streamline field data collection and management.

In response to this need, we developed a mobile application that supports biodiversity data collection through geotagged images and automated mapping. A key feature of the app is its “upload later” function, which allows users to capture images in the field without requiring an active internet connection—an essential function for remote or forested environments. Once connected, the captured photos can be uploaded into the application and automatically mapped by utilizing the geotagged information embedded in each photo, thereby enabling efficient visualization of spatial data. To explore the potential of artificial intelligence, the application also incorporates Google Vision AI, which provides general object recognition (e.g., birds, flowers, mammals). While not sufficient for species-level identification, this feature represents an initial step toward AI-assisted biodiversity monitoring, with future work focusing on developing tailored models for finer taxonomic resolution. To explore the potential of artificial intelligence, the application also incorporates Google Vision AI, which provides general object recognition (e.g., birds, flowers, mammals). While not sufficient for species-level identification, this feature represents an initial step toward AI-assisted biodiversity monitoring, with future work focusing on developing tailored models for finer taxonomic resolution.

Literature Review

Biodiversity inventories serve as structured records of species and habitats, forming the foundation for conservation planning and ecological research. While these inventories vary from simple checklists to systematic population assessments, their reliability is shaped by observer expertise, environmental variability, and methodological consistency (Association of Fish & Wildlife Agencies, 2018). Traditional inventories, often conducted by experts, generate high-quality data but are time-intensive and geographically limited. Conversely, opportunistic observations can expand spatial coverage but are frequently inconsistent, leading to issues of data completeness and comparability (Stephenson, 2020). This tension underscores a central challenge: conservation demands large-scale, up-to-date biodiversity data, yet conventional methods struggle to deliver both scale and accuracy simultaneously. Citizen science has emerged as a complementary solution to these limitations by mobilizing public participation in ecological monitoring. Large-scale platforms demonstrate the feasibility of this approach. For instance, WildLIVE! combined citizen-contributed data with machine learning to track wildlife dynamics, highlighting how public participation can generate datasets otherwise unattainable by professional monitoring alone (Jansen et al., 2024). Similarly, projects integrating image and sound recordings with AI have shown promise for near real-time bird species identification (Ovaskainen et al., 2024). However, while these projects demonstrate scalability, data quality remains uneven, particularly when volunteers lack taxonomic expertise (Hecker et al., 2018). Thus, while citizen science expands reach and engagement, it also introduces challenges in ensuring reliability and standardization.

Mobile applications are increasingly central to citizen science, offering tools for real-time reporting, geolocation tagging, and community sharing. Their accessibility reduces barriers to participation, but their scientific utility depends heavily on the balance between ease of use and data accuracy (Haklay et al., 2021). For example, iNaturalist has successfully integrated assisted recognition by suggestion function, which seems like an AI-training phase, hinting to the future AI integration. iNaturalist prioritize expert validation and GBIF data sharing, producing an unparalleled global biodiversity dataset (Irwin, 2018; Cohn, 2019). Yet, despite its scale, iNaturalist data often cluster around urban and accessible areas, leading to geographic bias. In contrast, eBird has addressed data quality more rigorously through automated filters and expert review, enabling its use in robust ecological models (Sullivan et al., 2014). However, its taxonomic scope is limited to birds, reducing its applicability to broader biodiversity monitoring. Meanwhile, Seek by iNaturalist focuses more on education and awareness than scientific contribution, showing how design priorities (engagement vs. data quality) influence project outcomes (Tewksbury et al., 2022). Taken together, these examples reveal the trade-offs between scale, quality, and scope that mobile apps must navigate.

Recent technological advances, such as environmental DNA (eDNA), drones, and GIS, have broadened the capacity for biodiversity monitoring. eDNA, for instance, allows detection of species without direct observation, enabling cost-effective monitoring of elusive or invasive species (Larson et al., 2020). Remote sensing and GIS mapping extend monitoring to landscape and ecosystem levels, complementing ground-based citizen science (Wang & Gamon, 2019). Artificial intelligence further supports these efforts by processing large datasets, identifying ecological patterns, and assisting with taxonomic classification (Rathoure & Ram, 2024). Yet, while AI offers efficiency, its accuracy remains contingent on high-quality training datasets—something often lacking for many understudied taxa (Stephenson, 2020). This suggests that the promise of AI-enabled citizen science is not in replacing expert taxonomy but in augmenting public contributions with automated assistance.

Citizen science also has tangible conservation impacts. In Germany, the integration of citizen and expert data improved understanding of large carnivore movements, directly influencing management strategies (Ludolphy et al., 2024). Similarly, citizen reporting of roadkill in India has informed infrastructure modifications, reducing wildlife mortality (Pawgi et al., 2024). Importantly, citizen science has broadened the taxonomic scope of conservation, such as spider monitoring in India, which has brought attention to overlooked invertebrate groups (Barve et al., 2024). Nevertheless, these examples also reveal uneven success: while some projects influence policy directly, others remain confined to educational value or awareness-raising without strong links to management action.

The reviewed literature demonstrates both the promise and limitations of citizen science in biodiversity monitoring. On one hand, mobile applications and emerging technologies have dramatically expanded data collection potential. On the other, issues of data quality, geographic bias, and limited taxonomic resolution persist. Most existing platforms assume continuous internet connectivity, which constrains their use in remote, biodiversity-rich environments. Similarly, while AI integration is growing, current models—such as Google Vision—are typically restricted to broad object recognition and lack specificity for species-level identification. This highlights the need for mobile solutions that combine offline functionality, automated geotagged mapping, and exploratory AI tools, bridging the gap between ease of public participation and the scientific rigor needed for effective biodiversity inventories.

Methodology

a. Benchmarking of Existing Applications

A benchmarking analysis was conducted on three widely used citizen science mobile applications—iNaturalist, eBird, and Seek—over a one-month period. Identical datasets consisting of animal (e.g., domestic cat) and plant images with embedded geolocation metadata were tested across the platforms. The evaluation focused on three criteria:

- Species identification accuracy – whether the mobile application could correctly identify the uploaded images.
- Location metadata extraction – whether geotag information was consistently and reliably extracted.
- Data validation mechanisms – how submitted observations were verified for accuracy.

The analysis revealed two critical limitations. First, location metadata extraction was inconsistent: many applications allowed uploads without embedded GPS data, forcing users to enter coordinates manually, which often resulted in erroneous records (iNaturalist Community Forum, 2019). Such inaccuracies compromise spatial data reliability, which is essential for ecological studies and conservation planning (Hunter, 2012). Second, validation processes were limited. For example, iNaturalist assigns "research grade" status after only three community confirmations, a process that may be insufficient for rare or ambiguous observations (iNaturalist Community Forum, 2019).

b. BioMap System Design:

In response to these limitations, a new mobile application—BioMap—was designed with a minimalist, user-friendly interface consisting of four main modules: Upload Image, Explore Map, Contributor ID, and Database Viewer. The design adopted a modular development approach, enabling each function to be built and updated independently to improve flexibility and maintainability.

A key design feature is the "upload-later" capability, which allows users to capture geotagged images in the field without internet connectivity and upload them once connected. The application enforces spatial data integrity by rejecting images without embedded GPS coordinates. Furthermore, BioMap introduces a dual-flag validation mechanism, whereby users can mark observations with a blue flag (likely valid) or red flag (likely invalid). Flag counts are stored in real time, ensuring that data reliability improves through collective validation while fostering user engagement.

c. Tools

The development of the BioMap mobile application for Android was supported by four main tools and services (Figure 1). Flutter 3.16.0 was used as the main development framework, providing a structured environment for building the app interface and core functionalities. For backend storage, Firebase Firestore was implemented as the cloud database to manage uploaded images and their associated metadata, including geographic coordinates, contributor IDs, and validation flags. To enable spatial visualization, the Google Maps API was integrated for automated mapping of geotagged images, allowing users to interactively explore biodiversity records. Finally, the Google Cloud Vision API was employed to perform general object recognition, offering preliminary identification labels (e.g., plant, bird, flower) that users can refine when submitting observations.

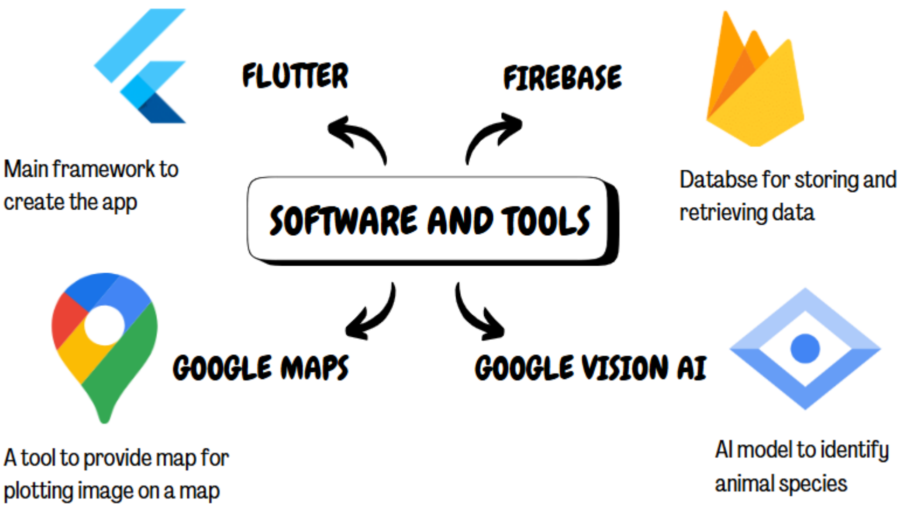


Figure 1: The tools for the apps development

d. Application flowchart

The functional workflow of the BioMap mobile application is presented in Figure 2. Upon initial launch, the system verifies whether a Contributor ID has been registered. If not, the user is prompted to create one, ensuring that all submissions can be properly attributed and traced back to their contributors. Once registered, the user gains access to the home interface, which provides four primary modules: Upload Image, Explore Map, View Database, and Contributor ID – as visualized as use-case diagram in Figure 3.

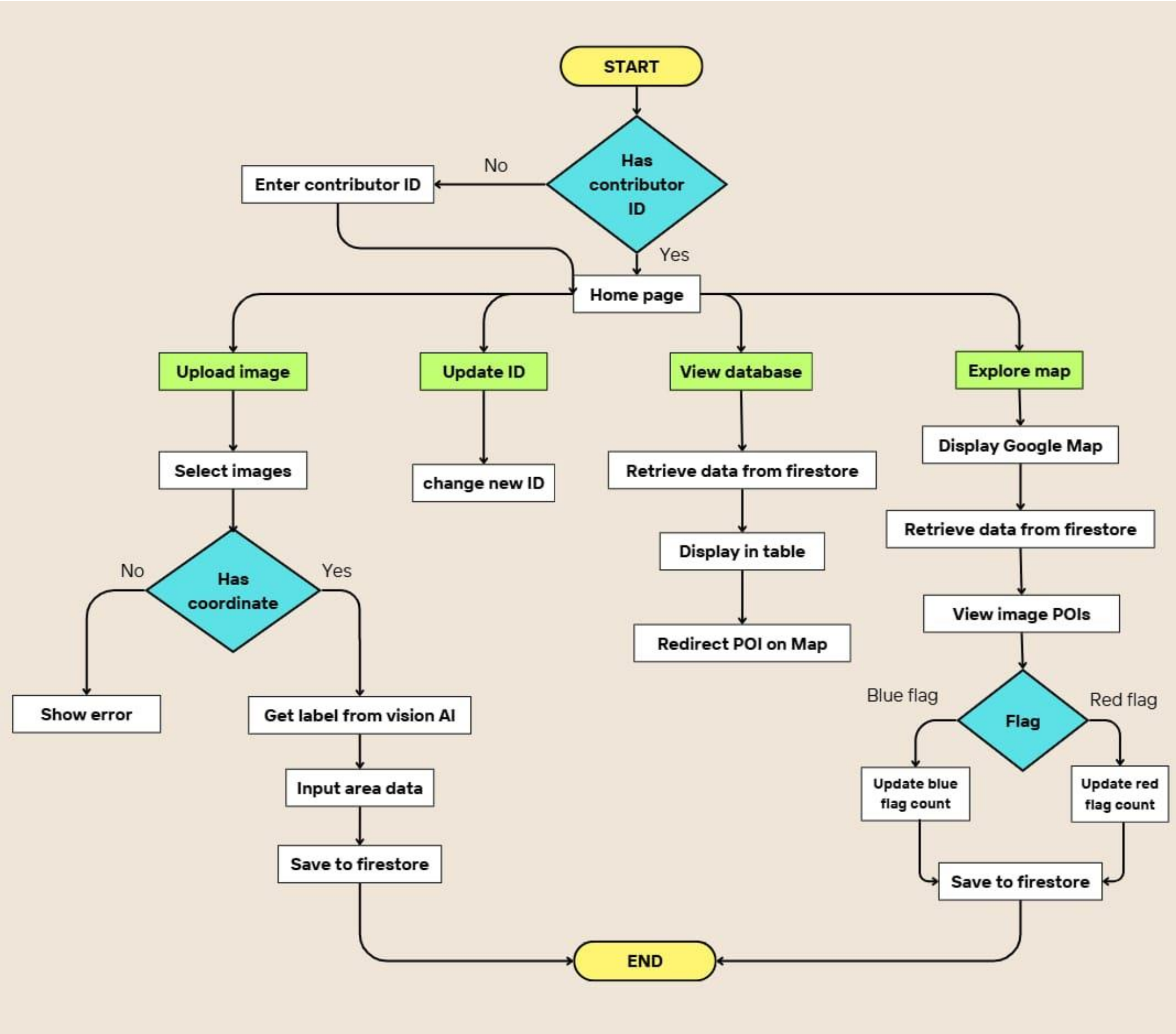


Figure 2: The flow of the process in using the BioMap apps for bioversity spatial inventory.

Within the Upload Image module, users may select one or more images from their device gallery. To safeguard spatial accuracy, the system validates the presence of embedded GPS metadata, automatically rejecting submissions without location information. For valid entries, additional metadata such as time and date are extracted, after which Google Vision AI provides a preliminary label. Users are given the option to confirm or revise the label before final submission. The completed dataset—including the image, metadata, Contributor ID, and validation flags—is then stored in Firebase Firestore, enabling real-time synchronization across devices. The Contributor ID module offers flexibility by allowing users to modify their identifiers when necessary, while maintaining consistency in data attribution. The View Database function provides tabular access to all uploaded records, displaying key attributes such as species label, coordinates, timestamps, contributor ID, and validation status. From the database, users can also navigate directly to the mapped location of a given record.

The most interactive component is the Explore Map module, which visualizes geotagged submissions through the Google Maps API. Each record is represented by a customized marker, allowing users to access associated metadata and contribute to a dual validation flagging process. Blue flags signal agreement with a record's accuracy, while red flags highlight potential errors.

Together, these functions establish an integrated workflow that emphasizes spatial data integrity, user-driven validation, and intuitive interaction. By combining automated verification with community participation, BioMap enhances both the reliability and usability of biodiversity data collected through citizen science.

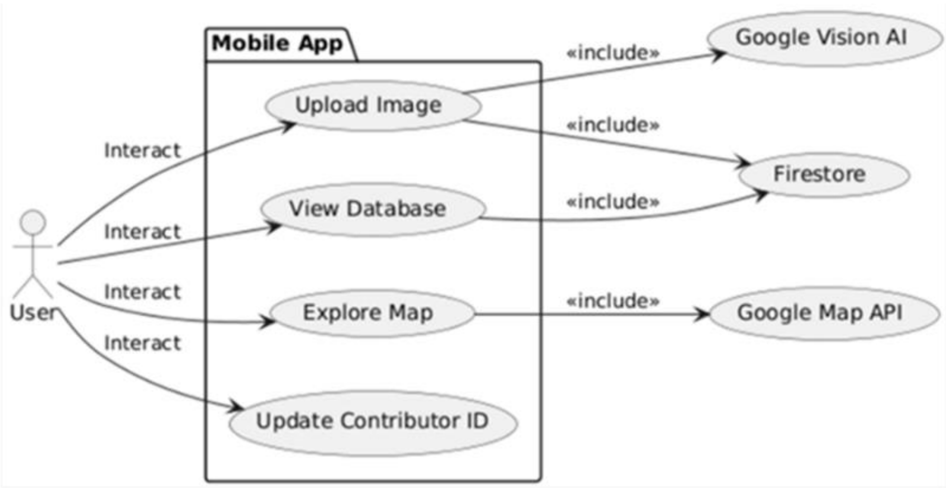


Figure 3: The use-case for user in BioMap

e. Testing and Deployment

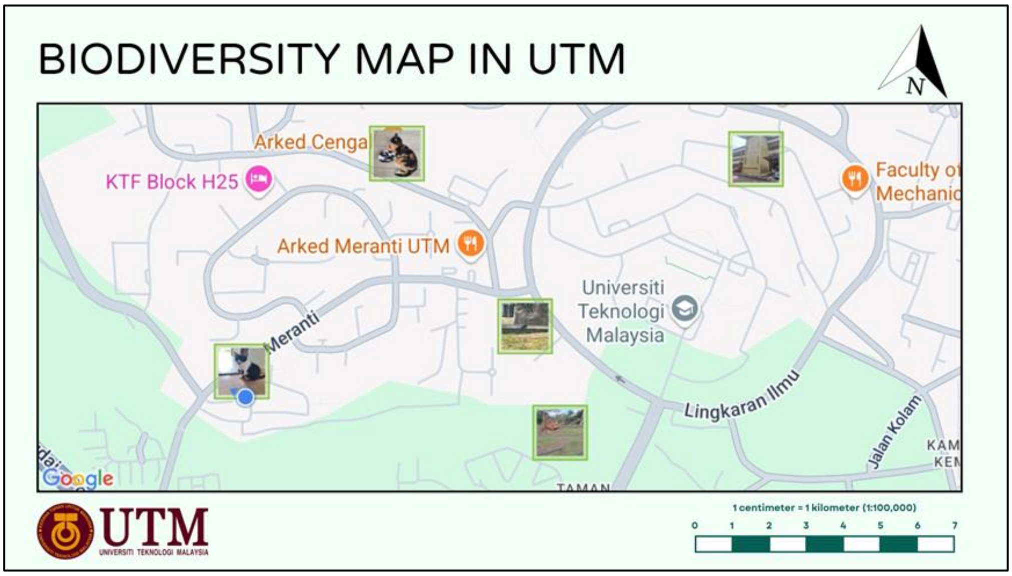
BioMap underwent iterative testing. Initial testing was conducted on Universiti Teknologi Malaysia (UTM) campus to verify core functionalities, including real-time synchronization, GPS metadata extraction, and AI-based image labeling. Field testing was subsequently performed twice in Hutan Simpan Panti Tinggi, Johor, a biodiversity-rich forest reserve. Multiple devices were used to evaluate performance under realistic conditions.

User feedback was also collected to assess usability and effectiveness. Results indicated that the enforced GPS requirement successfully eliminated erroneous spatial data, and the dual-flag validation system was well-received as a participatory quality-control mechanism.

Results and Discussion

a. Location extraction from geotagged photos

The application successfully extracted GPS coordinates from uploaded images and displayed them accurately on the map interface. Even when multiple images were taken at nearby coordinates, the system effectively separated the markers, preventing them from clustering into a single point. For improved visualization, the uploaded image itself was used as the map marker rather than the default red pin, allowing users to quickly recognize the content of each record. Figures 4 (a) and 4 (b) illustrate the spatial distribution of test data collected in Universiti Teknologi Malaysia (UTM) and Hutan Panti, respectively.



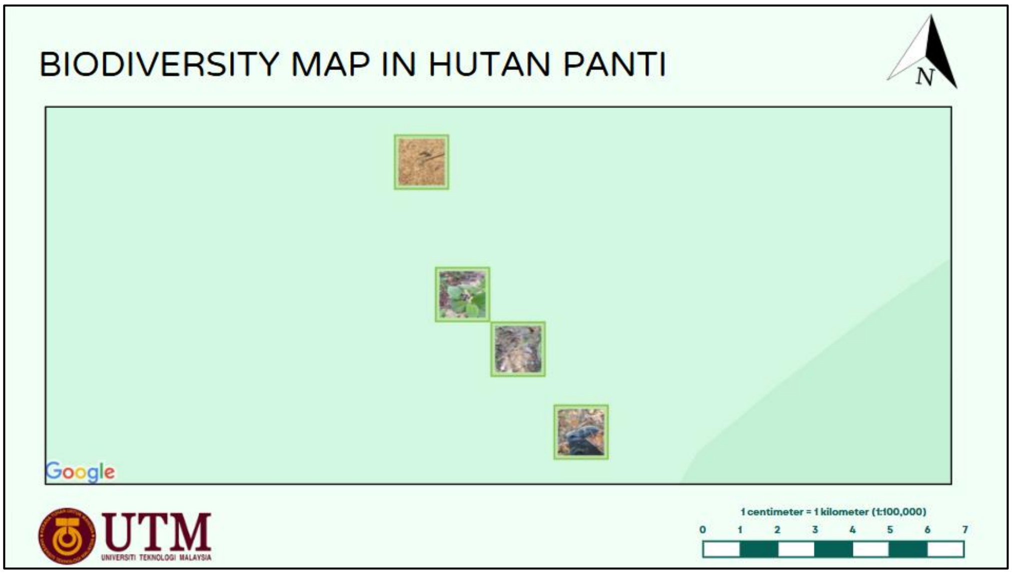


Figure 4(a) 4(b): The apps testing and automated mapping results for photos captured in UTM and Hutan Panti respectively

b. Automated feature identification from geotagged photos

The integration of Google Vision AI enabled generalized species classification (e.g., "dog," "cat," "plant") with reasonable accuracy. In several trials, BioMap demonstrated stronger performance than iNaturalist, particularly in identifying common animals such as dogs. For instance, in one test case, iNaturalist suggested possible species such as squirrel, pig, or cat, without identifying a dog (Figure 5(a)), whereas BioMap correctly provided "dog" as the primary suggestion as shown in Figure 5(b). While iNaturalist leverages a computer vision model trained on millions of user-verified images and incorporates spatiotemporal filters to refine predictions (iNaturalist Community, 2019), BioMap's streamlined use of Google Vision AI proved more effective in certain contexts.

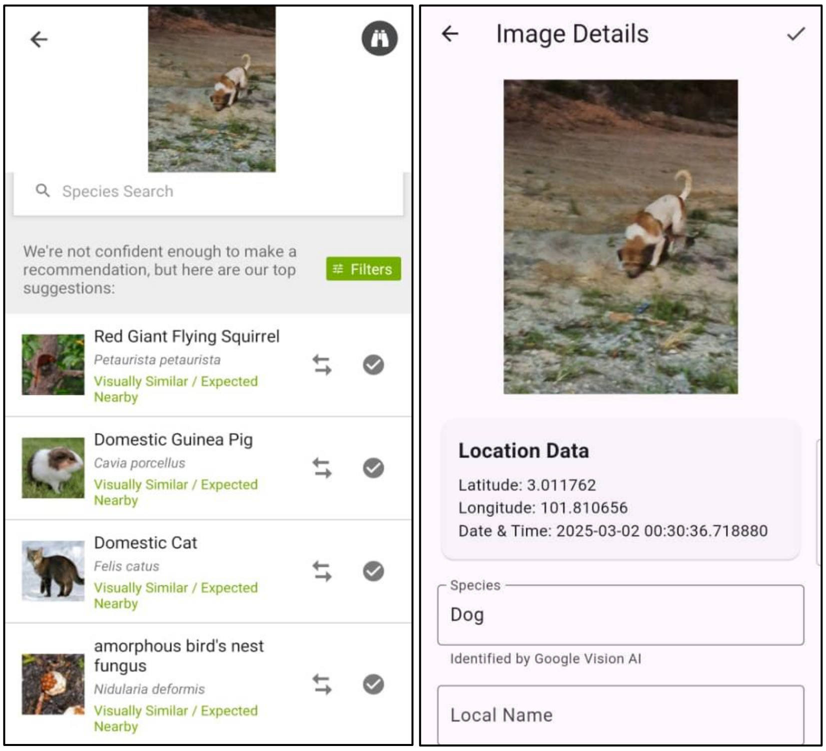


Figure 5: Comparison of identification function of same image on both INaturalist (5a) and BioMap (5b).

c. Comparative analysis

A benchmark analysis was conducted to evaluate BioMap against iNaturalist, a widely used citizen science platform, to validate the significance of the developed application. The comparison focused on three core criteria essential for biodiversity data quality: general identification, validation system, and location extraction. These functions are critical for ensuring accurate species recognition, reliable data verification, and precise spatial representation in citizen science applications.

For general identification, BioMap relies on Google Vision AI, which provides broad species category recognition (e.g., “dog,” “plant”). iNaturalist, in contrast, employs a computer vision model trained on millions of community-verified images, but its performance is still closely tied to its extensive species library and the integration of contextual information such as location and date. Suggestions are refined through expert verification and crowd-sourced feedback, which help improve accuracy over time, but the system is not yet fully independent of human validation.

In terms of data validation, BioMap incorporates a dual-flag mechanism, allowing contributors to mark records as either correct (blue flag) or questionable (red flag), with results instantly reflected in the system. iNaturalist adopts a community-driven validation process, where an observation is considered “research grade” once three or more users agree on the identification.

For location extraction, BioMap enforces strict spatial accuracy by accepting only images with embedded GPS metadata, ensuring geotag integrity. iNaturalist permits uploads without GPS information but compensates by allowing contributors to manually specify the location of their observation.

Table 1: Comparison between Biomap and Inaturalist

Criteria	Biomap	I Naturalist
General Identification	Uses Google Vision AI for general species categories	In the phase of AI model training with crowd sourced feedback to provide specific species names
Validation System	Offers flagging mechanism for validation	State an image as research grade if three people or more support it
Location plotting	Only allows uploads if GPS metadata is present	Allows upload without GPS but requests manual input

d. Application testing

Two forms of testing were conducted to assess the usability of the developed application. The first test focused on location accuracy, which was carried out by the research team through cross-checking the mapped positions against field notes and memory of the original image capture sites. This verification confirmed that the application consistently extracted correct geotagged information, with accuracy dependent on the device’s GPS and averaging within a margin of ±4 meters. This level of precision is largely attributable to the Android phone’s internal GPS receiver — and should be interpreted cautiously, since different phone models may produce different geolocation accuracies (e.g., smartphone GNSS receivers have been shown to achieve median horizontal accuracy of ~0.9 to 3.4 m under open-sky conditions) (Osborne et al., 2025). All uploaded images were successfully verified and mapped within the correct capture areas.

In addition to positional accuracy, **user feedback** was collected after each data submission. Key aspects evaluated included ease of use (via a star-rating system), the reliability of AI-generated general labels for uploaded images, system responsiveness (latency), and the alignment between mapped and original locations. A summary of these user evaluations is presented in Table 2.

Table 2: The user feedback on the app's performance

No	Features	Results		
1	Easiness of use	4 stars (average)		
2	Latency	4 stars (average)		
		Accurate	Average	Inaccurate
3	Satisfaction on general label generated by Google Vision AI	40%	60%	0%
4	Satisfaction on mapped location	70%	30%	0%

Conclusion and Recommendation

This study demonstrates that integrating modern technologies such as Artificial Intelligence (AI), Geographic Information Systems (GIS), and cloud computing can substantially enhance citizen science applications for biodiversity data collection. The developed BioMap mobile application addressed common limitations of existing platforms by introducing two key innovations: automated geotag validation and a dual-flag user validation system. The mandatory GPS metadata check ensured that only spatially reliable images were uploaded, thereby reducing risks of false or misplaced records. The dual-flagging mechanism enabled contributors to collectively verify observations, improving both data reliability and participant engagement. Complemented by a streamlined interface and real-time synchronization through Firebase Firestore, BioMap provides a user-friendly yet robust platform for community-driven biodiversity monitoring.

Despite these contributions, several limitations and opportunities for enhancement were identified. First, reliance on commercial APIs such as Google Vision AI and Google Maps introduces constraints due to limited free usage quotas. Future development should prioritize either securing academic or non-profit API credits from technology providers, or adopting open-source alternatives that can be hosted locally to reduce operational costs.

Second, while Firebase Firestore enabled real-time synchronization, its scalability is restricted under high-volume usage. Migrating to more flexible backend solutions—such as Google Cloud with expanded quotas, or local database systems (e.g., MySQL, MongoDB)—would improve data storage capacity and support larger user bases.

Third, BioMap's species identification currently relies on Google Vision AI, which is optimized for broad object recognition rather than biodiversity-specific classification. To improve scientific value, future iterations should incorporate custom machine learning models trained on local species datasets. Such models, developed in collaboration with academic or conservation institutions, would enable more accurate species-level recognition, moving beyond generic categories like "plant" or "dog."

In summary, BioMap provides a practical and scalable approach to citizen science for biodiversity monitoring. By addressing current limitations—particularly in species identification and data scalability—future iterations have the potential to contribute more directly to conservation research and policy through reliable, community-driven biodiversity data.

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