A COMPUTER VISION AND MAPS AIDED TOOL FOR CAMPUS NAVIGATION

An Undergraduate Research Scholars Thesis

by

ALEXANDER HALL

Submitted to the LAUNCH: Undergraduate Research office at
Texas A&M University
in partial fulfillment of requirements for the designation as an

UNDERGRADUATE RESEARCH SCHOLAR

Approved by
Faculty Research Advisor: Shinjiro Sueda

May 2022

Major: Computer Science

RESEARCH COMPLIANCE CERTIFICATION

I, Alexander Hall, certify that all research compliance requirements related to this Undergraduate Research Scholars thesis have been addressed with my Research Faculty Advisor prior to the collection of any data used in this final thesis submission.

This project required approval from the Texas A&M University Research Compliance & Biosafety office.

TAMU IRB #: 2022-0021D Approval Date: 02/14/2022 Expiration Date: 02/13/2023

TABLE OF CONTENTS

ABSTRACT

A Computer Vision and Maps Aided Tool for Campus Navigation

Alexander Hall
Department of Computer Science
Texas A&M University

Research Faculty Advisor: Dr. Shinjiro Sueda
Department of Computer Science
Texas A&M University

Current study abroad trips rely on students utilizing GPS directions and digital maps for navigation. While GPS-based navigation may be more straightforward and easier for some to use than traditional paper maps, studies have shown that GPS-based navigation may be associated with disengagement with the environment, hindering the development of spatial knowledge and development of a mental representation or cognitive map of the area. If one of the outcomes of a study abroad trip is not only to navigate to the location, but also to learn about important features such as urban configurations and architectural style, then there needs to be a better solution than students only following GPS directions.

This research introduces one such explored solution being a new feature within wayfinding mobile applications that emphasizes engagement with landmarks during navigation. This feature, powered by computer vision, was integrated into a newly developed wayfinding mobile application, and allows one to take pictures of various Texas A&M University buildings and retrieve information about them. Following the development of the mobile application, a user study was conducted to determine the effects of the presence or absence of this building

recognition feature and GPS-based navigation on spatial cognition and cognitive mapping performance. Additionally, the study explores the wayfinding accuracy performance of the building recognition feature and GPS-based navigation compared with traditional paper maps.

This paper includes preliminary results where it was found that groups without GPS-based navigation took longer routes to find destinations than those with GPS-based navigation. It was also found that cognitive mapping performance improved for all participants when identifying destination buildings. Final data collection and analysis is planned for April 2022.

DEDICATION

To my faculty advisor, research team, and family who supported me throughout this endeavor.

ACKNOWLEDGEMENTS

Contributors

I would like to thank my faculty advisor, Dr. Sueda for giving me the opportunity to conduct this research and giving me advice and support throughout the course of this research. I have learned so much working with him and appreciate his guidance.

I would also like to thank Dr. Dongying Li from the Department of Landscape Architecture & Urban Planning for providing me background information in environmental psychology, helping to construct the user study, and key insights throughout the course of this research.

Thank you to Dr. Galen Newman from the Department of Landscape Architecture & Urban Planning for providing feedback and key insights on the study and app design.

Thank you to fellow undergraduate Kaylin Slaughter from the Department of Landscape Architecture & Urban Planning for designing the user interface and providing key insights into app design.

Thanks also go to my friends and colleagues and the department faculty and staff for making my time at Texas A&M University a great experience.

The images used for the image classification model were provided by Dr. Sueda and his graduate students, Dr. Li, Kaylin Slaughter, and me.

All other work conducted for the thesis was completed by the student independently.

Funding Sources

Undergraduate research was supported by Dr. Dongying Li et al. as part of the Texas A&M Global Engagement Grant, A5: The Augmented Atlas for Architecture and Landscape Architecture Abroad. Its contents are solely the responsibility of the authors.

1. INTRODUCTION

Wayfinding mobile applications have become pervasive across society today. According to one 2018 study, over 75% of all smartphone owners regularly use wayfinding apps [1]. With currently over 80% of the world's population owning a smartphone [2], this amounts to roughly over 60% of the world utilizing wayfinding apps. With such a large userbase, it is important that wayfinding apps function optimally and provide a quality user experience. While wayfinding apps provide great functionality in the form of being able to navigate to a desired destination, their strong reliance on GPS-based navigation may diminish the ability to form spatial knowledge as will come to be described further on in this section.

The remaining portion of this section will offer background in spatial cognition and modern wayfinding mobile applications to understand the need for the computer-vision-powered contextual awareness feature as integrated within the newly created TAMU Building Seeker wayfinding app.

1.1 Spatial Cognition Background

In cognitive and environmental psychology, spatial cognition is generally defined as how people collect, organize, use, and revise information about their environment. Psychologists Edward Tolman and Clark Hull were pioneers in this area becoming the first to perform research in animal 's spatial representation, behaviors, and learning [3].

Later, environmental features were explored as ways to facilitate the acquisition of spatial information and aid people in accomplishing their everyday tasks. Urban theorist Kevin Lynch (1960) proposed that there are five physical elements that aid in forming a mental image of one's surroundings: paths, edges, districts, nodes, and landmarks [4]. These features become especially important in the context of wayfinding which will be discussed later.

Further supporting the importance of the physical elements described by Lynch, the Landmark-Route-Survey (LRS) model came to be described by Seigel and White (1975) [5]. As a way to describe the representation of spatial knowledge, the LRS model states that an observer first takes note of discrete landmarks akin to nodes, then constructs connections (edges) between them by developing route knowledge, and finally gains survey knowledge as the graph defined by landmarks and routes is made more distinct.

While both landmarks and routes have a role to play in the representation of spatial knowledge, there exists an ongoing debate between landmark-based and route-based knowledge acquisition.

1.1.1 Cognitive Mapping and Sketch Maps

Cognitive mapping is described as the process of acquiring, amalgamating, and storing information to form a comprehensive representation of the environment. The result of this process is called a cognitive map which can be used as a basis to study people's representation of spatial information [6]. Cognitive maps may vary in form with some being based more on Euclidean or cardinal directions while others are based on more on graphs or relationships. One type of externally represented cognitive map is a sketch map, where a subject will sketch their environment following a learning task. Sketch maps can be used to provide information perceived by the sketcher such as dominant functions in a locale, ordinal information, the regularity of features, and frames of reference [7]. An example of a sketch map taken from the user study conducted in this research is shown in Figure 1.1.

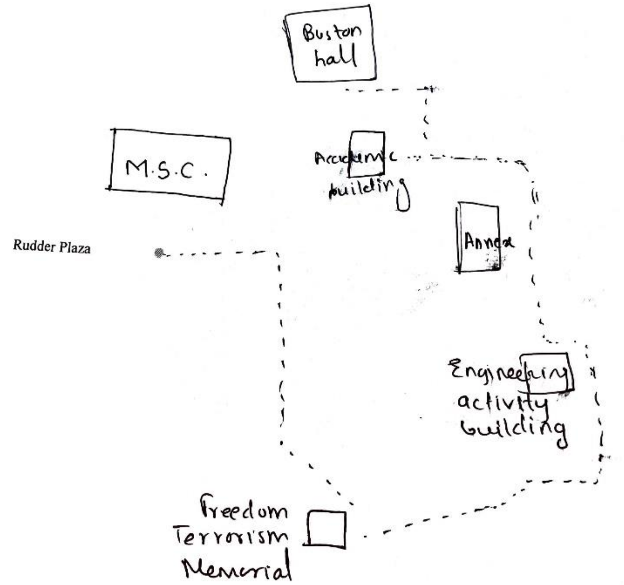

Figure 1.1: Example sketch map from the conducted pre-study.

1.1.2 Landmarks and Their Role in Navigation

With landmarks being one of the five physical elements described by Lynch and the first component to acquiring spatial knowledge as proposed by the LRS model, they hold importance within the realm of spatial cognition. Across urban design planning and literature, landmarks have been taken to mean objects that stand out in environments and can serve as points of reference. Given this definition, it can be assumed landmarks have an important role to play in navigation as well. Indeed, it has been proposed that landmarks hold four distinct roles as navigational aids: as beacons, orientation cues, associative cues, and frames of reference [8]. This multi-factor role landmarks have in navigation lends them to be a key include in modern wayfinding applications.

1.2 Current Wayfinding Mobile Applications

Many modern wayfinding mobile applications share a similar set of features. To offer some preliminary background, this section will outline the foundational technology behind wayfinding apps being GPS then discuss the role of digital maps in wayfinding.

1.2.1 Global Positioning System (GPS)

GPS is the U.S.-based satellite-powered navigation system which provides geolocation data to GPS receivers. To further aid cellular devices in quickly and accurately obtaining a geolocation, cellular devices also utilize other location-based technologies such as a Wi-Fi positioning system and triangulation from nearby cellular towers [9]. This system, called Assisted GPS (A-GPS) makes obtaining geolocations more reliable in locations where satellites are not able to send a clear signal.

1.2.2 Digital Maps in Wayfinding

Digital maps make up the core feature of a modern wayfinding application. At their most basic form, digital maps use GPS to display accurate, real-time geographical information. As opposed to their paper counterparts, digital maps typically allow more than a fixed map visual by allowing one to scroll and zoom out to reveal additional map coverage. Such features make them great choices for navigation, but there are even more features supplied by current wayfinding mobile applications to enhance the standard digital map functionality. Common digital map and wayfinding supporting features include markers to label points of interest, visual or audio turn-by-turn navigation, real-time traffic data, and estimated time of arrival [10]. These features, among others, provide an informed way to perform a wayfinding task, however as we will see in the next section, there exist limitations in this scheme as it pertains to spatial memory.

1.3 Issue with Current Wayfinding Mobile Applications

As current wayfinding mobile applications rely so heavily on GPS-based navigation, there is a sparse amount of interaction users have with their external environment. Furthermore, in a study conducted by neuroscientists, Louisa Dahmani and Véronique D. Bohbot, it was found that extensive GPS use led to a decline in spatial memory [11]. The study goes on to describe how this effect was observed in several aspects of spatial memory including the extent by which spatial memory strategies were used, cognitive mapping, landmark encoding, and learning. In an experiential learning setting, this can be particularly detrimental as a decline in spatial memory leads to a reduced ability to gain context and learn about one's surroundings.

1.4 Proposed Solution: A Computer-Vision-Powered Contextual Awareness Feature

To resolve the issue that GPS-based navigation poses in an experiential learning setting, this paper proposes the addition of a computer-vision-powered contextual awareness feature for landmark detection. As described earlier on, landmarks play a key role in forming a cognitive map as well as aiding in navigation. This being the case, they would serve well to form the foundation for a context awareness feature in a wayfinding mobile application. We propose a context awareness feature that would utilize image classification to allow for one to take a picture of a nearby building or landscape feature and retrieve the name and accompanying information of the landmark detected in the image.

1.4.1 Previous Work in Image Classification of Buildings

Existing research in image classification of buildings has focused on general classification of buildings into related groups. For example, the use of recurrent neural networks to classify encoded contextual information from building images isolated using bounding boxes has been used to classify buildings as commercial, residential, public, and industrial [12]. In a different study also classifying buildings into categories, two convolutional neural networks were applied to classify traditional East Asian buildings as being either from China, Korea, or Japan [13].

These examples of image classification to classify buildings into related bins is appropriate for their proposed use cases being in a broader setting. The image classification model created as part of the research outlined in this paper deviates from this common theme as it is designed for the recognition of specific named buildings. As such, the bins of the image classification model comprise the names of individual buildings as opposed to general categories.

1.5 Objectives

We seek to determine whether a contextual awareness feature with GPS-based navigation will improve cognitive mapping performance compared to traditional paper maps and GPS-based navigation without a contextual awareness feature. Additionally, we seek to determine whether GPS-based navigation improves wayfinding accuracy of important landmarks compared to traditional paper maps.

2. METHODS

In this section, we will outline the user study design, overall app design, and provide background for the image classification machine learning model and related logic.

2.1 Overview

To test the proposal for a computer vision based contextual awareness feature which relays information about buildings recognized in images, the TAMU Building Seeker app was developed. TAMU Building Seeker is a wayfinding mobile application which contains two major features:

1. A navigation feature through a digital map with enabled routing.
2. A building recognition feature which allows the ability to take pictures of campus buildings and landscape features at Texas A&M University and retrieve the name and information of the landmark depicted in the image.

The latter represents the context awareness feature which is hypothesized to aid in spatial cognition and the formation of spatial knowledge.

To test this hypothesis, a trial user study accompanied the app whereby participants were each given a paper map, asked to download the TAMU Building Seeker app, and utilize both to navigate to three fixed destinations in Texas A&M. Depending on which group a participant was discreetly assigned, the app would enable or disabled each of the two major features. In this way, the effects of GPS-based navigation and the context awareness feature can be more accurately determined. Additionally, participants were asked to fill out questionnaires before, during, and after navigating campus to assess their spatial knowledge development.

2.2 User Study Design

The user study formed the foundation for obtaining results via the use of questionnaires and the custom-built mobile application. The following sections will outline further details into the each of the major study components.

2.2.1 User Study Groups

As mentioned in the overview, user study groups were determined by the enabling and disabling of the two major features of the mobile app. Each group was then asked to navigate a fixed route given the features that were available to them. These groups and the general study flow are as defined in Figure 2.1 below.

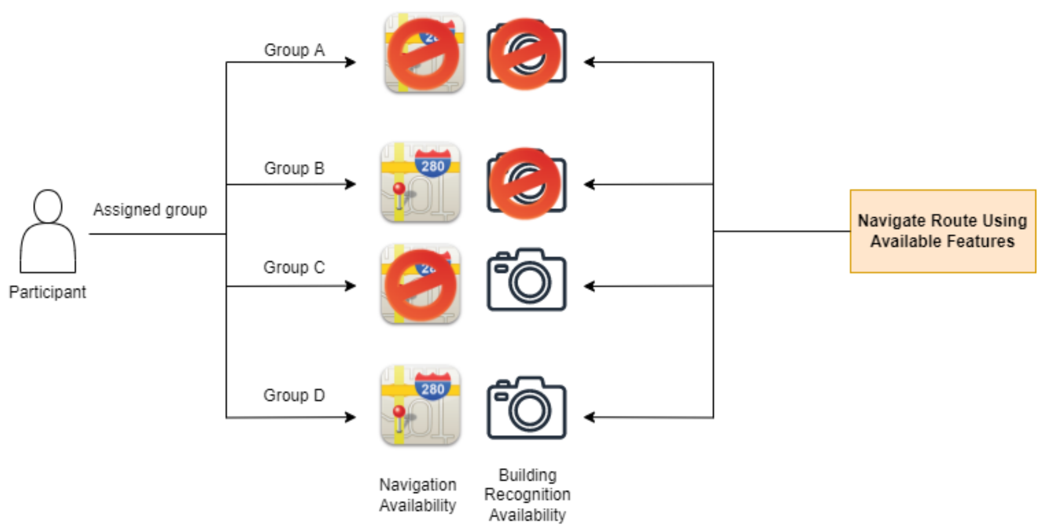

Figure 2.1: User study groups and study flow

Group A does not have access to neither GPS-based navigation nor the building recognition feature, group B only has access to GPS-based navigation, group C only has access to the building recognition feature, and group D has access to both features. Additionally, each participant, regardless of group, was given a paper map to further aid in navigation in the case that they did not have GPS-based navigation.

2.2.2 Walking Route

One constant factor among all participants was which destinations each participant would be navigating towards and the order of these destinations. This, however, left some variation as to which route the participant would take to these destinations. The general route was defined to begin at Rudder Plaza, go to the Freedom from Terrorism Memorial, go to the Engineering Activity Buildings, go to Bolton Hall, then finish back at Rudder Plaza. The locations of these destinations would be unknown to the participant based on the results of a pre-screening questionnaire.

While the route was only explicitly given to participants in groups with the digital maps feature enabled, those without this feature were still asked to the same destinations using the paper map and building recognition feature if enabled. Figure 2.2 displays the optimal path a participant can take to reach each of the three destinations in the route. At a minimum, this would take approximately 15 minutes to navigate.

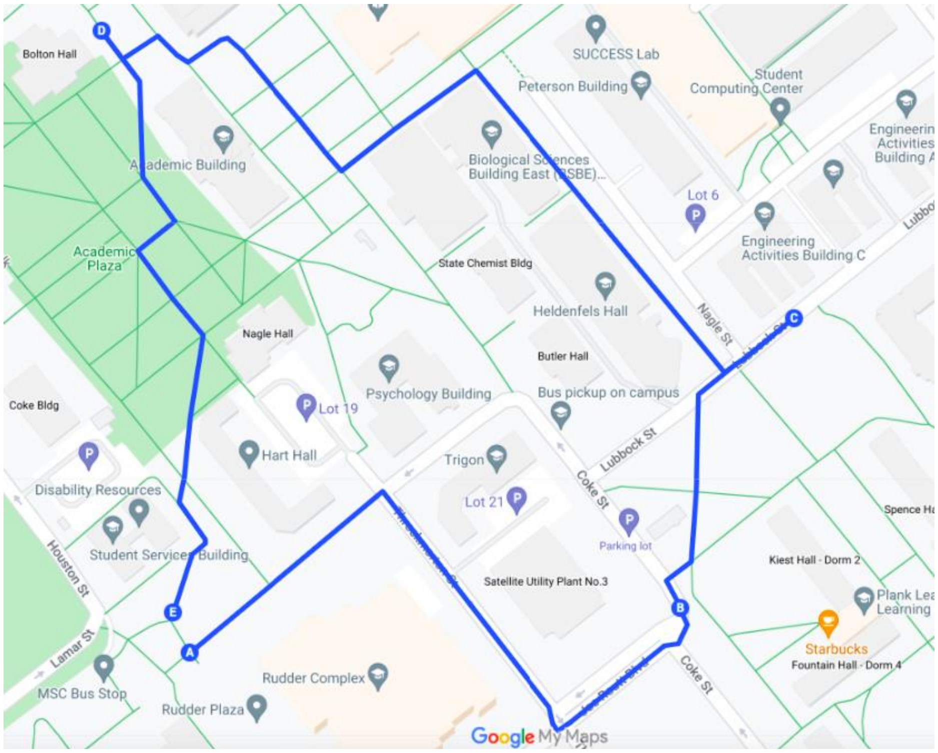

Figure 2.2: User Study Preset Route

2.2.3 Questionnaires

Given that the research question focuses on the psychological effects of a contextual awareness feature in wayfinding applications, there was also a need for qualitative data. As such, several questionnaires were designed to assess the participant's feelings and experiences throughout stages of the study.

For screening potential participants, we designed a pre-screening questionnaire to ensure we had no biases in our participants and that the participants did not know the location of the three destination buildings of the study route. Before the user was asked to navigate the route, they were given a pre-questionnaire which was used to obtain information on their previous wayfinding experience and wayfinding methods used. Additionally, the participant was asked to draw a cognitive map of what they thought the campus looked like from their current location.

This was to help eliminate false positives and to compare with an additional cognitive map they would draw at the end of the study.

As the user navigated the route, they were prompted with a mid-questionnaire within the app after arriving at each destination in the route. This questionnaire aimed to find out the participant's sentiments at that point in time.

After completing the route, the user was again asked to draw a cognitive map through a post-questionnaire. This would be compared to the pre-questionnaire cognitive map to note any changes since before using the app. Additionally, this questionnaire would ask for opinions on the overall app design and determine which wayfinding cues they used throughout navigation.

2.3 App Design

The main constraints on app design focused on supported features and desired app functionality. For the former, the machine learning model creation software we utilized, CreateML [14], was limited to the generation of models for iPhone and iPad devices. As such, we chose those devices running iOS 15.0 or higher as the medium for the new app. For the desired app functionality, we knew we wanted the user study groups to differ in terms of app functionality, therefore much of the app is designed with the ability to enable or disabled features based on a group code inputted at the beginning. These being the largest constraints, there was flexibility to be had regarding app user interface, implementation of major features, supported minor features, and data collection methods.

2.3.1 App User Interface

Depending on whether the user had access to the navigation feature or not, the layout of the user interface differed. As one set of groups was able to use maps-guided routing, much of the app flow and functionality was available on the maps view itself whereas the other set of groups navigated the route using features available entirely on the homepage. The following subsections will provide details on the user interface, discuss any surface-level logic behind them, and outline key distinctions between different user study groups.

2.3.2 Major Features

The major features of this app were the features which were disabled or enabled based on which user study group each participant was assigned to. These being the maps-aided navigation and the building recognition feature.

2.3.2.1 Maps-Aided Navigation

The maps-aided navigation feature was designed to be a standard digital maps feature that might be found in any modern wayfinding application with little changes. Powered by Apple's MapKit framework which integrated a simple version of Apple Maps, the maps feature would draw the most optimal route from the user's current location to their next destination in the walking route as seen in Figure 2.3.

Figure 2.3: Maps-Aided Navigation Feature

Additionally, the maps feature would further support participants with this feature enabled by notifying them when they were 60 meters within one of the destinations. This notification is shown in Figure 2.4 below.

Figure 2.4: Nearby Destination Notification

2.3.2.2 Campus Building Recognition

The campus building recognition feature is the second major feature within the app which is toggled between the user study groups. This serves as the contextual awareness feature and adds on top of traditional wayfinding apps. This feature allows a user to use a "Take Photo" button to take a picture of a building and retrieve context about that building. This flow is depicted in Figure 2.5.

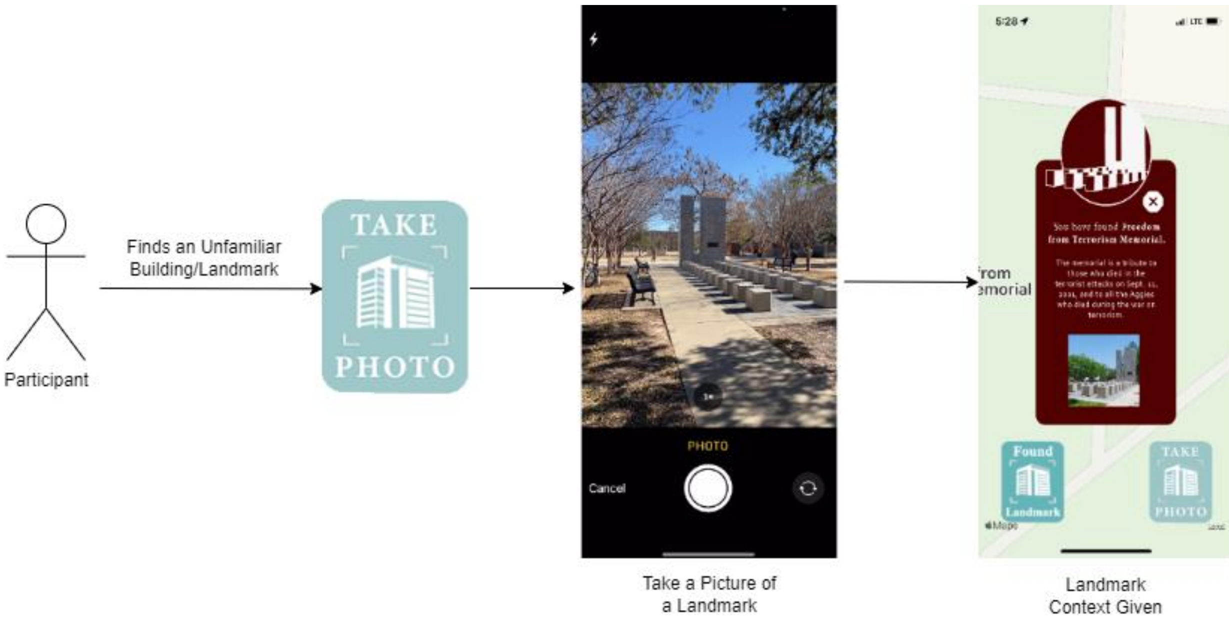

Figure 2.5: Campus Building Recognition Feature

2.3.3 Minor Features

The minor features of the app are accessible by all user study groups and aid in either data collection, app functionality, or user support.

2.3.3.1 Group Code Input

Before beginning the user study, the research team will have randomized four-letter codes for each participant. This code will be entered into the app by the participant which will then determine their group based on the second letter of that code (A/B/C/D).

2.3.3.2 Supporting Features

Accessible by all user study groups are three supporting features: a list of the buildings in the route with available information, a tutorial on how to take a picture of a building, and a photo bank. The picture-taking tutorial in specific holds the most importance among these features as it offers the participant guidelines on how to take a photo consistent with how the machine learning model was trained. These being images captured with the entire building in frame and having no obstructions. Figure 2.6 depicts how these supporting features are shown in the app.

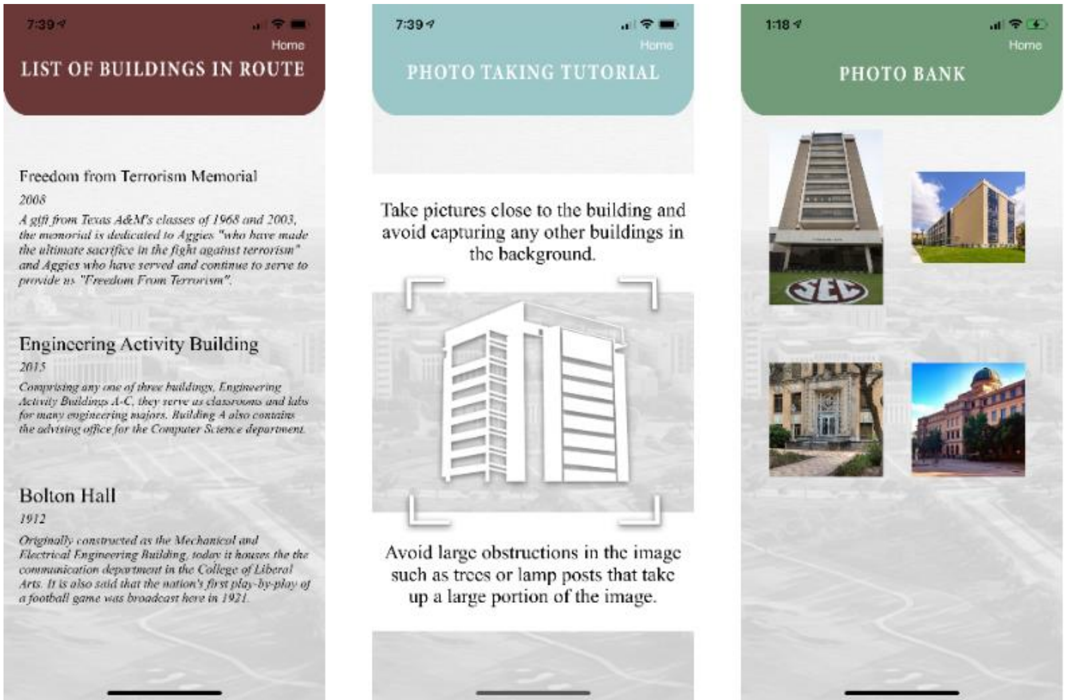

Figure 2.6: The Three Common App Features

2.3.3.3 Destination Arrival Confirmation

When the participant arrives at one of the three destinations in the walking route, the researcher must know if they truly did arrive at the destination or not. To verify this, every participant is asked to take a picture of what they think the destination building is once they arrive using the “Found Landmark” button. The image classification model in conjunction with the user’s current location is then used to verify that the user arrived whereupon the user is prompted to complete one of the mid-questionnaires. The general flow is depicted in Figure 2.7 below.

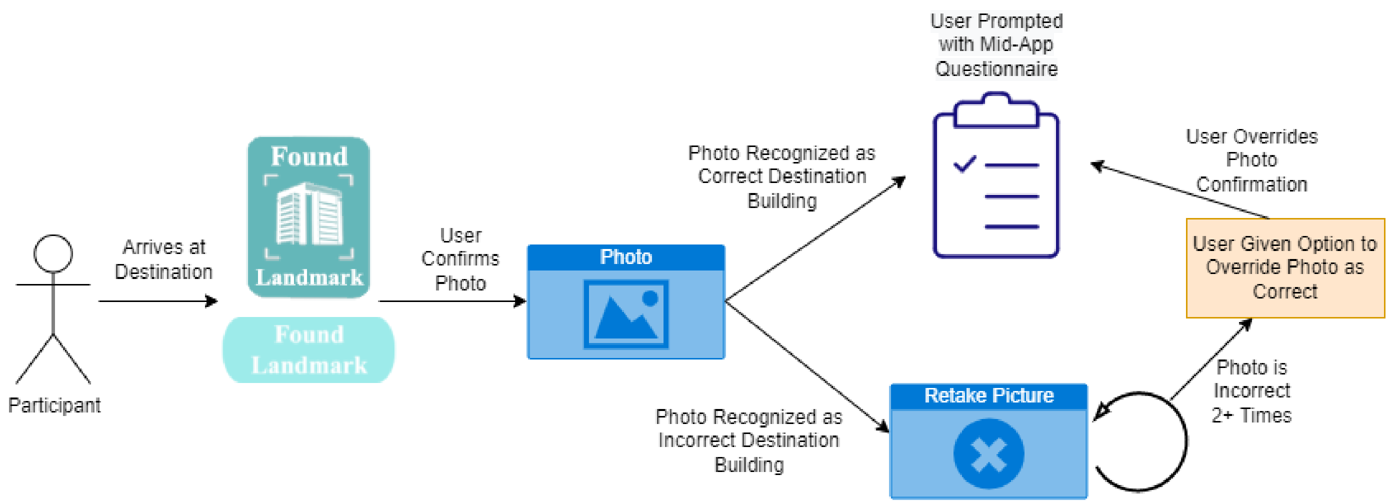

Figure 2.7: Destination Arrival Confirmation Flow

2.3.3.4 Remote ML Model Integration

One feature that allows for on-the-fly changes to the machine learning model to be integrated within the mobile app is the Remote ML Model Integration Feature. This feature allows the researcher to make changes to the machine learning model, upload them to cloud storage, then download that model to the participant's phone when the app is launched. This means that if more buildings are desired to be detected, then the app version does not need to be updated. The flow for this is depicted in Figure 2.8.

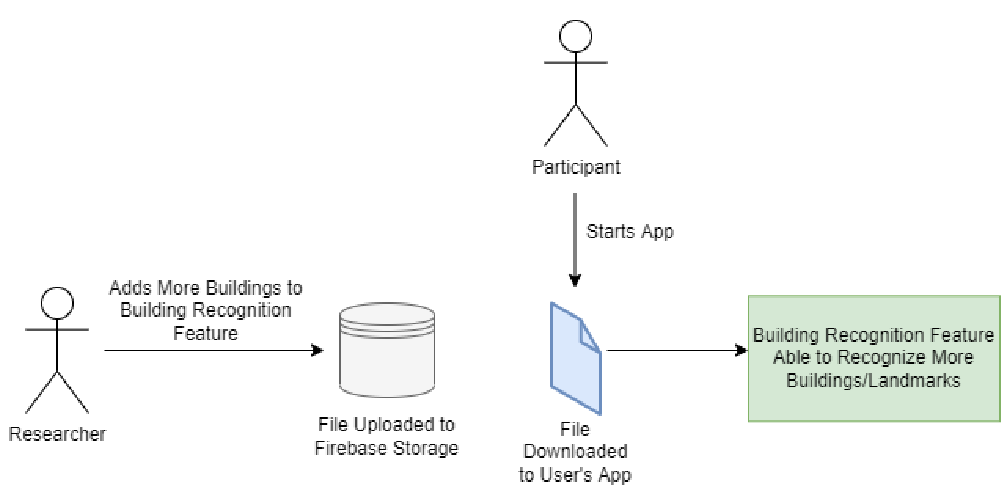

Figure 2.8: Remote ML Model Integration Feature Flow

2.3.4 App Data Collection Methods

Various types of data were collected while the participate utilized the TAMU Building Seeker app during the study. This quantitative data was used for analyzing the accuracy of the user when walking to a destination, verifying usage of the building recognition feature, and obtaining mid-questionnaire results. Table 2.1 displays all data metrics taken from the app as the user navigates the study route.

Table 2.1: Types of Data Collected

Data	Format	Additional Information
Timestamped Coordinates	{ ((latitude, longitude), datetime, seconds elapsed), … }	Starts after the participant opens the map or clicks start.
Destination Times	(seconds elapsed, …)	Taken when the participant takes a correct picture of the destination or after two incorrect picture taking attempts.
Number of Pictures Taken	Integer value	Taken after using the “Found Landmark” button or the “Take Photo” button
Number of Destination Pictures Taken	Integer value	Taken after the “Found Landmark” button is used
Number of Times Building Recognition Feature Used	Integer value	Taken after the “Take Photo” button is used
Number of Times Building Recognition Feature is Successful	Integer value	Defined as whether the recognized building post-classification processing is the closest building to the participant (see Figure 2.9 for post-classification processing algorithm)
Number of Times Destination Building Recognized	Integer value	Defined as whether the recognized building was in the list of classification results (see Figure 2.10 for how this combined list is defined)
Successful Destination Building Recognition Times	(seconds elapsed, …)	Taken after the “Found Landmark” button yields a found destination

Failed Destination Building Recognition Times	(seconds elapsed, …)	Taken after the "Found Landmark" button yields a found destination
Survey Results	[(Q1 string response…Q4 string response), …]	Taken after each survey is completed within the app (three times)
Survey Start Time	Integer value	Taken after the "Start" button is pressed for groups A and C. After "Building Seeker" or "My Location" is pressed for groups B and D
Survey End Time	Integer value	Taken after the final survey is complete following the third destination
Group	A/B/C/D	Taken as the second letter of Group Code
Group Code	X(A/B/C/D)XX	At the beginning upon code input

2.4 Detection of Campus Buildings

A major feature of the study is the ability for the participant to retrieve information about campus buildings and landscape features represented in images taken in the TAMU Building Seeker app. Additionally, there must be a method for the researcher to be able to detect when the participant arrives at each of the three destinations in the route. These necessities introduce the need for the ability to detect which campus building or landmark is detected in an image which is achieved using an image classification ML model.

2.4.1 Image Classification Machine Learning Model

An existing machine learning model provided through the Create ML software was utilized. This underlying model is called `VisionFeaturePrint_Screen`. It was developed by training on an expansive dataset and can be used to extract 2,048 features from an image. Transfer learning is then used to construct a new model by reusing this feature detection capability from `VisionFeaturePrint_Screen` on our provided image dataset. This cuts down upon the time it takes to train a neural network from the ground up.

2.4.1.1 Image Augmentations

In addition to providing an underlying model, Create ML also gave the option to perform image augmentations to generate a larger dataset and improve training accuracy. The provided options that were used were: noise, blur, crop, expose, flip, and rotate. The specific implementation of these is not specified in the documentation and may subsequently be a source of classification accuracy error.

2.4.2 Image Data Collection

With the need to train a new model and the lack of a large enough dataset of various Texas A&M buildings and landscape feature images publicly available, this generated the need to manually collect and construct an image dataset. This ultimately led to the research team collecting over 4,500 images of 35 different Texas A&M buildings and landscape features across campus. This dataset is publicly available in the team's Google Drive found here.

2.4.2.1 Image Criterion

To keep data consistency and to simulate the ideal conditions present during the participant's navigation of the route, there were specific criteria for an image to be included in the dataset. These included:

- Image taken in daytime with sunny or cloudy weather conditions
- Entire section of building from ground to top of building present in image; not zoomed in
- No major obstructions in the image such as trees, shadows, or large groups of people

Additionally, images were taken from all sides of the building or landscape feature to capture cases where a participant may approach a building from any angle.

2.4.3 Improving Classification Result Accuracy

As the Create ML program used to train the model used did not allow for modifications to the number of layers and provided fixed, pre-defined image augmentations, classification accuracy could only be improved by modifying the number or quality of images in the dataset. As such, we devised algorithms to improve the ultimate output of how these accuracies were used within the TAMU Building Seeker app. The two ways of doing this were by location filtering and image splitting as outlined in the next subsections. taking into the participant's current location after classification and splitting the app-captured image into multiple chunks and applying the algorithm on each chunk.

2.4.3.1 Location Filtering

After retrieving classification results of the overall image (or of a chunk of the image as described in the next section), these results were filtered to include only landmarks within 60 m of the participant. To achieve this, the coordinates of the center of all 35 Texas A&M buildings and landscape features represented in the ML model were stored. Then the distance from the participant's precise location to this each of these landmark coordinates were calculated and filtered.

2.4.3.2 Image Splitting

To improve accuracy of the building recognized in the image, the original image was split into a three-by-three grid composed of nine squares. The top three most frequently present landmarks in all chunks filtered by location are taken as the chopped image results. The general algorithm for this is shown in Figure 2.9.

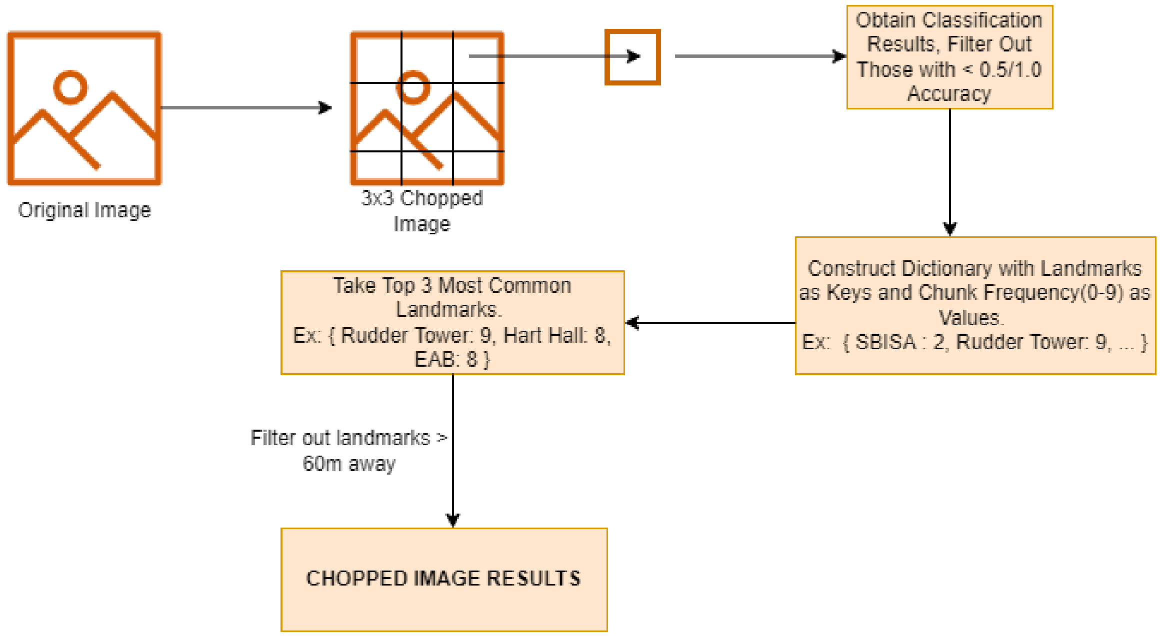

Figure 2.9: Image Splitting Algorithm Flow

2.4.4 Classification Result Post-Processing Algorithm

Utilizing the whole image classification results and the chopped image classification results, these are both used to determine:

- The landmark present in the image when using the building recognition feature.
- If the landmark present in the captured destination image is a destination.

Depending on which of these two use cases is needed, the algorithm behaves differently. This discrepancy lies in that for the building recognition feature case, one exact landmark needs to be identified and presented to the participant while for the destination recognition case, an exact landmark is not necessary as user has found the destination and can therefore be laxer. The algorithm flow is depicted in Figure 2.10 below.

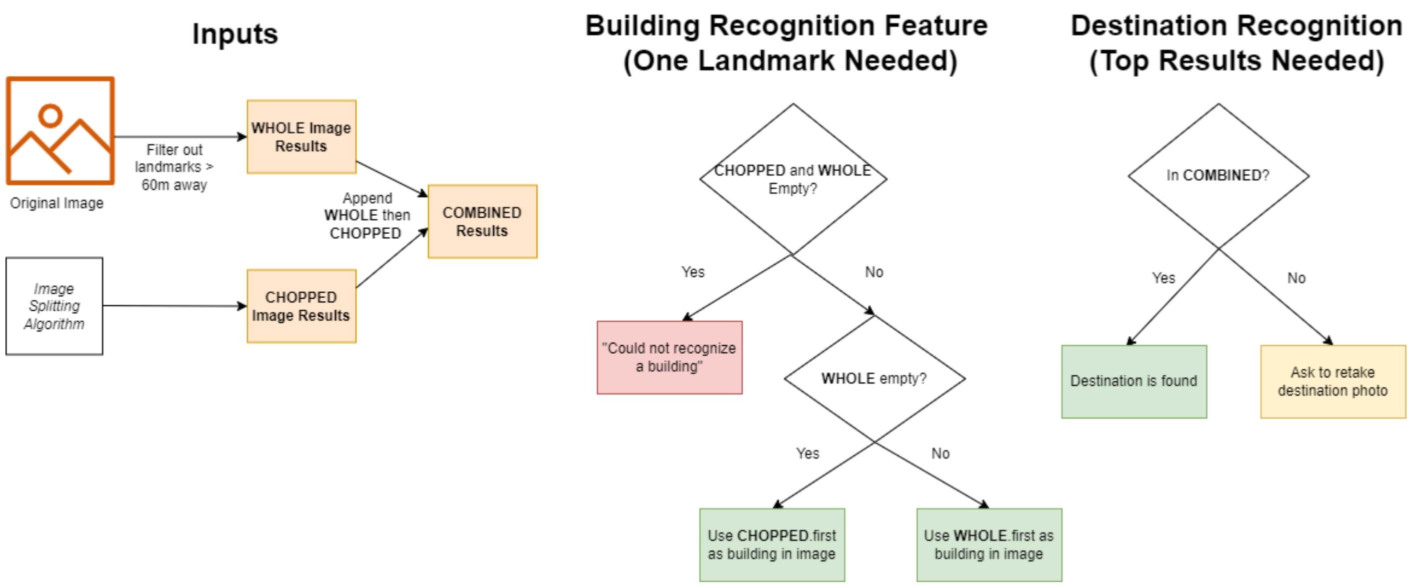

Figure 2.10: Image Classification Post-Processing Flows per Use-Case

The building recognition feature prioritizes the resulting classification of the whole image and defaults to the top classification of the chopped image results if a whole image classification was not found. For destination recognition, the whole image classification results and chopped image classification results were combined and if the destination was in the resulting list, the participant would be notified they found the destination, otherwise they would be asked to retake the photo.

3. RESULTS

The following sections describe the results of the trial user study in terms of questionnaire responses and wayfinding results and the image classification model accuracy.

3.1 User Study Results

As a preface, because the full user study will be conducted later in April 2022, the following user study results were obtained from a sample of only six participants from user study trials. This being the case, conclusions are extrapolated. Participant questionnaire results can additionally be found in Appendix B.

3.1.1 Questionnaire Responses

From the pre-questionnaire, it was found that from the responding participants, it was generally the case that they were somewhat anxious when navigating unfamiliar environments and that they typically use various wayfinding strategies in their everyday lives.

From the mid-questionnaire, it was found that participants were generally in an above average mood as they navigated to each destination, generally not anxious, had little difficulty finding the destination, and were generally not lost, regardless of user study group. One slight exception to this was the participant in group A who did express some feelings of being lost and anxious. This is predicted as group A participants do not have access to either major app feature and must rely on paper maps for navigation.

From the post-questionnaire, it was found that the app was generally easy to use and was found to have good visual aesthetic for all groups. Additionally, it was found that cognitive mapping accuracy generally improved for identifying positions of destination buildings compared to before navigating the route.

3.1.2 Wayfinding Results

From participants tested, it was generally found that groups with digital maps had fewer deviations when locating each destination. This contrasts with groups with only paper maps who went backwards at points in the route and took suboptimal routes. Figure 3.1 shows the walking routes each participant took separated by group. Breaks in the route or sporadic points can be attributed to internet connectivity issues.

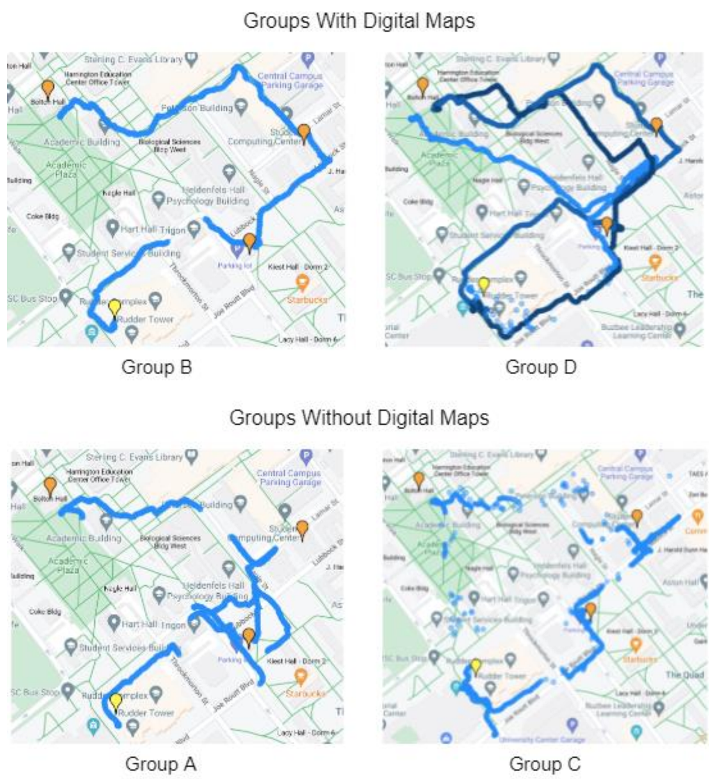

Figure 3.1: Participant Walking Routes by Group (Start in Yellow, Destinations in Orange)

Additionally, it was found that groups with digital maps were able to navigate to all three destinations faster than groups without digital maps. Table 3.1 shows the average total time elapsed to navigate to all three destinations by group and excluding time to complete mid-questionnaires.

Table 3.1: Participant Route Average Completion Time by Group

	Groups Without Digital Maps		**Groups With Digital Maps**	
	Group A	Group C	Group B	Group D
Total Time Elapsed(s)	1030.0	1840.0	958.0	965.0

From these trial wayfinding results, it can be estimated that GPS-based navigation outperforms only paper maps in terms of wayfinding accuracy.

3.2 Image Classification Model Accuracy

The two main ways to test accuracy of the model were the preliminary results given by Create ML software used to train the model and the results from the study itself.

3.2.1 Create ML Generated Accuracies

Create ML uses two metrics to determine: training accuracy and validation accuracy. Training accuracy is defined as how correctly the `VisionFeature_PrintScreen` algorithm determined the weights of features each image following all iterations. Validation accuracy is defined as being similarly to training accuracy, however it uses a subset of images from the full dataset used to prevent model overfitting [15]. Figure 3.1 shows the results of these two metrics after running 10 iterations through our generated dataset.

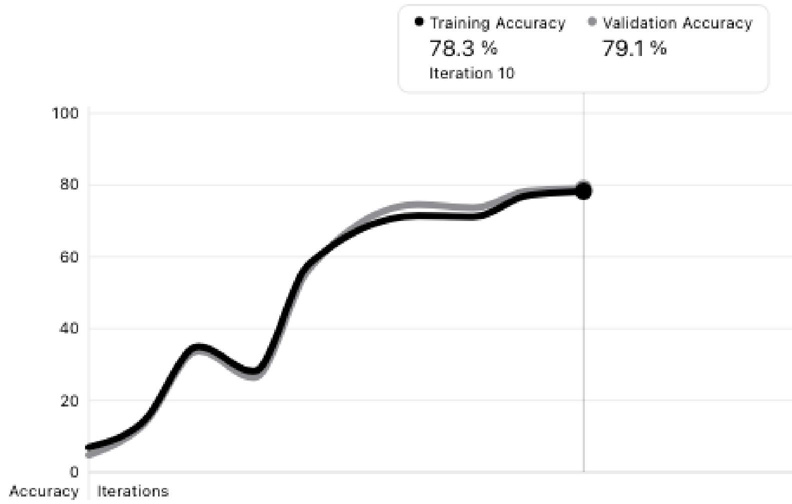

Figure 3.1: Image Classification Model Accuracies

This yielded a 78.3% training accuracy and a 79.1% validation accuracy. This accuracy is in line with previous research on image classification of buildings which has seen accuracies of around 80% [12]. Possible sources of error include the fewer number of iterations due to Create ML setting 10 iterations as the limit due to not being able to acquire more information about each image from the dataset.

3.2.2 Study Resulting ML Model Accuracies

From the study itself, counts of how many pictures were accurate and the total number of pictures taken were some of the metrics taken from the app. By dividing number of accurate photos by total number of photos taken for the respective metrics, the accuracies in Table 3.2 were determined.

Table 3.2: Study Building Recognition Accuracies

Building Recognition Feature Accuracy	0.318
Destination Recognition Accuracy	0.64

One possible source of error for both metrics includes images taken of zoomed-in landmarks where the participant was standing more than 60m away from them. Another possible source of error for building recognition feature accuracy is an image taken when the participant was standing closer to a similarly looking building than the building being pictured. Finally, the dataset used to train the model may have been a source of error as it may not have been expansive enough.

4. CONCLUSION

This paper introduced an issue with GPS-based navigation within an experiential learning context. This being that it disengages its user from their physical surroundings which leads to hindered spatial cognition and subsequently the reduced ability to learn about features in their environment. As a solution, this paper proposed the introduction of a contextual awareness feature within wayfinding mobile applications that serves to promote the user's engagement with landmarks in their physical surroundings. Such a feature was described to allow a user to take a picture of a building or landscape feature and gain information about the recognized landmark. To implement this kind of feature, an image classification model would need to be developed.

This proposed feature was then developed in the context of Texas A&M University landmarks and implemented into a newly developed wayfinding mobile application. This application was then used in a user study to determine the effects of GPS-based navigation and this building recognition feature on cognitive mapping performance and wayfinding accuracy.

The study was conducted on a small group of participants whereupon it was extrapolated that GPS-based navigation outperformed traditional paper maps in terms of wayfinding accuracy. Additionally, it was deduced that cognitive mapping performance was enhanced for participants when describing the locations of route destination buildings.

The results of the image classification model and related post-classification algorithms powering the building detection feature were found to accurately be able to detect study destination buildings and somewhat accurately be able to detect any of the 35 buildings represented in the model. Limitations to the model were that the underlying algorithm and augmentations were pre-created for a wide variety of features rather than our use-case of buildings and landscape features. Optimizations that would be made given more time and resources would be to create a custom image classification model suited for Texas A&M University buildings and to refine our image splitting algorithm to dynamically segment images based on where features are present.

4.1 Future Work

Upcoming work in this study will look to gather more participants for the user study to gain statistically conclusive results regarding improved cognitive mapping accuracy and the differences between wayfinding and spatial cognitive performance of GPS-based navigation versus the building recognition feature. Additionally, the building recognition accuracy will be investigated and possible sources of error such as participant proximity to buildings and image classification dataset errors will be explored.

An additional extension of this research may be pursued as moving the study and building recognition features to the German study abroad program in Fall 2022.

REFERENCES

[1] R. Panko, "The Popularity of Google Maps: Trends in Navigation Apps in 2018 | August 2021," The Manifest, Jul. 10, 2018. https://themanifest.com/app-development/trends-navigation-apps (accessed Jan. 23, 2022).

[2] "Number of smartphone users from 2016 to 2021," Statista. https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/ (accessed Jan. 23, 2022).

[3] "spatial cognition," APA Dictionary of Psychology. 2020 American Psychological Association. Accessed: Jan. 22, 2022. [Online]. Available: https://dictionary.apa.org/spatial-cognition

[4] K. Lynch, The image of the city, 33. print. Cambridge, Mass.: M.I.T. Press, 2008.

[5] A. W. Siegel and S. H. White, "The Development of Spatial Representations of Large-Scale Environments," in Advances in Child Development and Behavior, vol. 10, H. W. Reese, Ed. JAI, 1975, pp. 9–55. doi: 10.1016/S0065-2407(08)60007-5.

[6] K. Manser, Image and Environment: Cognitive Mapping and Spatial Behavior edited by Roger M. Downs, David Stea. 2018.

[7] "Spatial Cognition, Cognitive Mapping, and Cognitive Maps," 2006. https://www.semanticscholar.org/paper/Spatial-Cognition%2C-Cognitive-Mapping%2C-and-Cognitive/65ebf8776fc24e77e524b589140ad24f621001a8 (accessed Jan. 23, 2022).

[8] E. Chan, O. Baumann, M. Bellgrove, and J. Mattingley, "From Objects to Landmarks: The Function of Visual Location Information in Spatial Navigation," Frontiers in Psychology, vol. 3, 2012, Accessed: Jan. 23, 2022. [Online]. Available: https://www.frontiersin.org/article/10.3389/fpsyg.2012.00304

[9] "What is Assisted GPS (A-GPS)? - Definition from Techopedia," Techopedia.com. http://www.techopedia.com/definition/24218/assisted-gps-a-gps (accessed Jan. 23, 2022).

[10] "Top 20 Free GPS Navigation Apps & Traffic Apps in 2022 | Sixt," SIXT rent a car Magazine, Jan. 25, 2021. https://www.sixt.com/magazine/tips/top-free-navigation-apps/

(accessed Jan. 23, 2022).

[11] L. Dahmani and V. D. Bohbot, “Habitual use of GPS negatively impacts spatial memory during self-guided navigation,” Sci Rep, vol. 10, no. 1, p. 6310, Apr. 2020, doi: 10.1038/s41598-020-62877-0.

[12] K. Zhao, Y. Liu, S. Hao, S. Lu, H. Liu, and L. Zhou, “Bounding Boxes Are All We Need: Street View Image Classification via Context Encoding of Detected Buildings,” IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1–17, 2022, doi: 10.1109/TGRS.2021.3064316.

[13] S.-Y. Ji and H.-J. Jun, “Deep Learning Model for Form Recognition and Structural Member Classification of East Asian Traditional Buildings,” Sustainability, vol. 12, no. 13, Art. no. 13, Jan. 2020, doi: 10.3390/su12135292.

[14] A. Inc, Create ML - Machine Learning. Apple Inc. Accessed: Jan. 24, 2022. [Online]. Available: https://developer.apple.com/machine-learning/create-ml/

[15] “Create ML Tutorial: Getting Started,” *raywenderlich.com*. https://www.raywenderlich.com/5653-create-ml-tutorial-getting-started (accessed Apr. 01, 2022).

APPENDIX: A – QUESTIONNAIRES

Please answer the following questions to determine whether you qualify for participating in this research.

1. Are you a Texas A&M student?
   □ Yes □ No

2. How long have you studied at Texas A&M University?
   □ <= 12 months □ 13-24 months □ 25-48 months □ >48 months

3. What is your age?
   □ <= 17 □ 18-25 □ 26-65 □ >66

4. Do you have an iPhone/iPad running iOS 15.0 or above? (How do I find out the version of ios on my device? Follow the steps here: https://support.apple.com/en-us/HT201685)
   □ Yes □ No

5. Select the Texas A&M buildings/landmarks from the list that you know the location of (Check all that apply)? Please do not look them up.
   □ Zachry Engineering Education Complex
   □ Clements Hall
   □ Freedom From Terrorism Memorial
   □ YMCA Building
   □ Haynes Engineering Building - HEB
   □ Biological Sciences Building East
   □ Bolton Hall
   □ Rudder Tower
   □ Michael T. Halbouty Geosciences Building
   □ Academic Building
   □ The Pavilion
   □ Military Sciences Building (Trigon)
   □ Blocker Building
   □ Engineering Activity Building
   □ Scoates Hall

Figure A.1: Pre-Screening Questionnaire

The following questionnaire contains 7 questions about how anxious you feel when you are in an unfamiliar environment. Please rate the level of anxiety you think you would feel in the following situations:

1. Deciding which direction to walk in an unfamiliar city or town after coming out of a train/bus/metro station or parking garage
□ Not at all anxious □ Not very anxious □ Neutral □ Somewhat anxious □ Very anxious
2. Finding my way to an appointment in an unfamiliar area of a city or town
□ Not at all anxious □ Not very anxious □ Neutral □ Somewhat anxious □ Very anxious
3. Leaving a store that I have been to for the first time and deciding which way to turn to get to a destination
□ Not at all anxious □ Not very anxious □ Neutral □ Somewhat anxious □ Very anxious
4. Finding my way back to a familiar area after realizing I have made a wrong turn and become lost while traveling
□ Not at all anxious □ Not very anxious □ Neutral □ Somewhat anxious □ Very anxious
5. Finding my way in an unfamiliar shopping mall, medical center, or large building complex
□ Not at all anxious □ Not very anxious □ Neutral □ Somewhat anxious □ Very anxious
6. Finding my way out of a complex arrangement of offices that I have visited for the first time Trying a new route that I think will be a shortcut, without a map
□ Not at all anxious □ Not very anxious □ Neutral □ Somewhat anxious □ Very anxious
7. Pointing in the direction of a place outside that someone wants to get to and has asked for directions, when I am in a windowless room
□ Not at all anxious □ Not very anxious □ Neutral □ Somewhat anxious □ Very anxious

The following questionnaire contains 14 questions about wayfinding strategies. Please rate how typical it is for you to use each of the following strategies.

1. I kept track of the direction (north, south, east or west) in which I was going
□ Not at all typical of me □ Not very typical of me □ Neutral □ Typical of me □ Very typical of me
2. Before starting, I asked for directions telling me whether to go east, west, north or south at particular streets or landmarks.
□ Not at all typical of me □ Not very typical of me □ Neutral □ Typical of me □ Very typical of me
3. Before starting, I asked for directions telling me whether to turn right or left at particular streets or landmarks.
□ Not at all typical of me □ Not very typical of me □ Neutral □ Typical of me □ Very typical of me
4. I kept track of where I was in relation to the sun (or moon) in the sky as I went.
□ Not at all typical of me □ Not very typical of me □ Neutral □ Typical of me □ Very typical of me
5. As I drove, I made a mental note of the mileage I traveled on different roads.
□ Not at all typical of me □ Not very typical of me □ Neutral □ Typical of me □ Very typical of me
6. Before starting, I asked for directions telling me how many streets to pass before making each turn.
□ Not at all typical of me □ Not very typical of me □ Neutral □ Typical of me □ Very typical of me
7. I kept track of the relationship between where I was and the center of town.
□ Not at all typical of me □ Not very typical of me □ Neutral □ Typical of me □ Very typical of me
8. Before starting, I asked for directions telling me how far to go in terms of mileage.
□ Not at all typical of me □ Not very typical of me □ Neutral □ Typical of me □ Very typical of me
9. As I drove, I made a mental note of the number of streets I passed before making each turn.
□ Not at all typical of me □ Not very typical of me □ Neutral □ Typical of me □ Very typical of me
10. I kept track of the relationship between where I was and the net place where I had to change my direction.
□ Not at all typical of me □ Not very typical of me □ Neutral □ Typical of me □ Very typical of me
11. I visualized a map or layout of the area in my mind as I drove.
□ Not at all typical of me □ Not very typical of me □ Neutral □ Typical of me □ Very typical of me
12. Before starting, I asked for a hand-drawn map of the area.
□ Not at all typical of me □ Not very typical of me □ Neutral □ Typical of me □ Very typical of me
13. I referred to a published road map.
□ Not at all typical of me □ Not very typical of me □ Neutral □ Typical of me □ Very typical of me
14. I made a mental note of landmarks, such as buildings or natural features, that I passed along the way.
□ Not at all typical of me □ Not very typical of me □ Neutral □ Typical of me □ Very typical of me

Next, we would like to know a little bit about you. All information you provide will stay confidential.

1. What is your gender?
□ Female
□ Male
□ Other
2. In what year were you born? ___________
3. Are you of Hispanic, Latino, or Spanish origin?
□ Yes
□ No
4. What is your race? Check one or more that apply.
□ White
□ African American
□ Asian
□ Native Hawaiian or Pacific Islander
□ American Indian or Alaska Native
□ Other
5. How long have you been studying at Texas A&M University at College Station?
□ 1 year
□ 2 years
□ 3 years
□ 4 years
□ 5 or more years
6. On average, how long do you stay on campus on weekdays?
□ Less than 1 hour
□ 1-2 hours
□ 3-4 hours
□ 5-8 hours
□ More than 8 hours

On this page, please draw a map that shows your impression of the Texas A&M main campus, with where we stand (the Rudder Plaza) as the center. Imagine that you are drawing the map for a family/friend who has never come to Texas A&M before, and would like to see the places on campus that you know.

Rudder Plaza

Figure A.2: Pre-Questionnaire

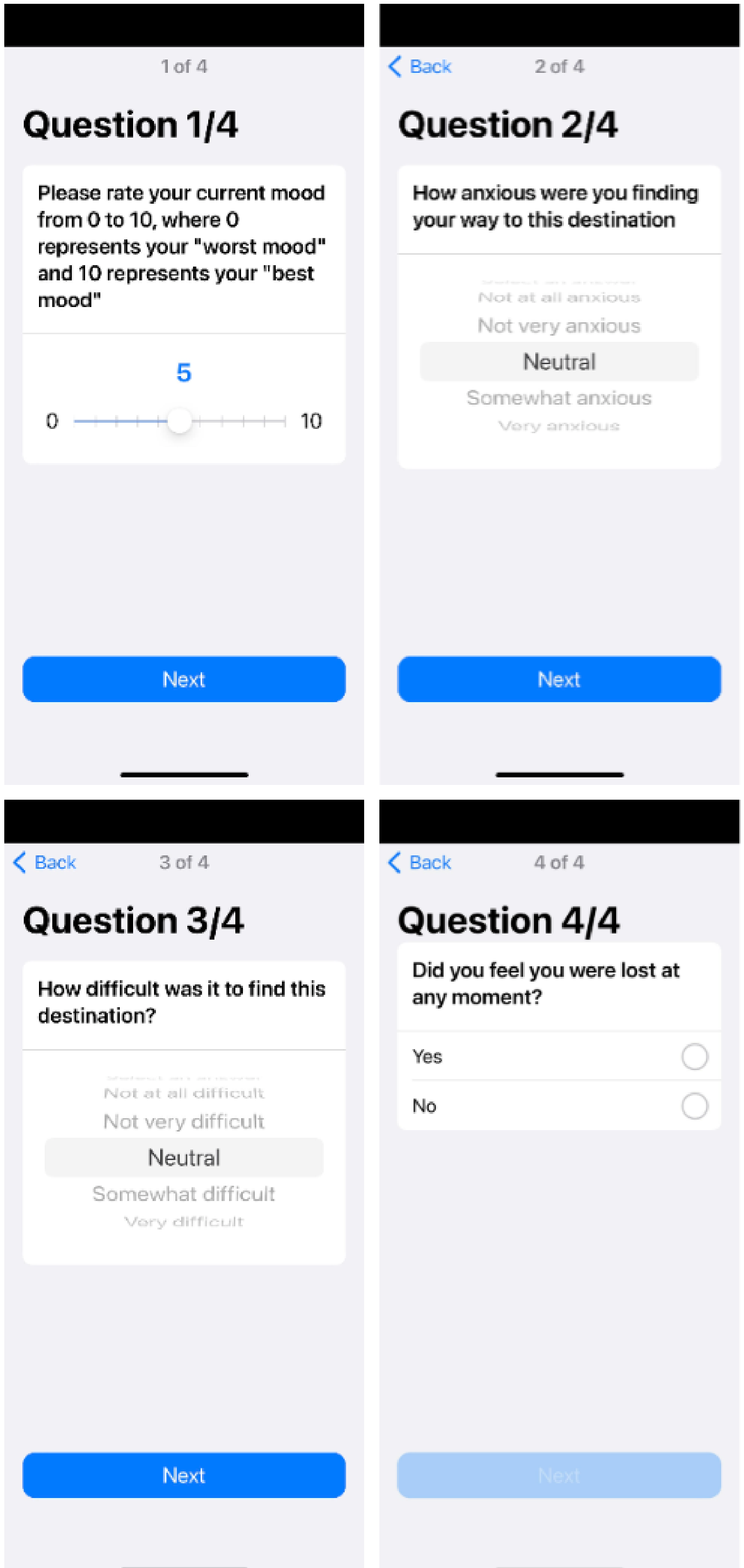

Figure A.3: Mid-Questionnaire (Within App)

The following questionnaire is about the usability and interface of the TAMU Building Seeker Application. It is currently under development, and we would like to hear your feedback:

1. What is your study code? ____
2. How difficult was it to find out where your next destination was?

   □ Very Difficult □ Moderately Difficult □ Neutral □ Moderately Easy □ Very Easy
3. Were all the features of the app obvious for you to use?

   □ Very Difficult □ Moderately Difficult □ Neutral □ Moderately Easy □ Very Easy
4. Were you satisfied with the visual aesthetic of the app? (Icons, backgrounds, etc.)

   □ Very Dissatisfied □ Moderately Dissatisfied □ Neutral □ Moderately Satisfied □ Very Satisfied
5. Did you ever need to retake your picture when you were taking a picture of the correct destination?
   □ Yes
   □ No
6. How beneficial was the picture taking feature in finding the destination?

   □ Very Hindering □ Moderately Hindering □ Neutral □ Moderately Beneficial □ Very Beneficial
7. What features would you like to see added in the app?

____

8. Did you notice any features (e.g., buildings, pathways, sculptures) that you have never noticed before?
   □ Yes
   □ No
9. What wayfinding cues did you use?
   □ Routing instructions on the app
   □ Maps on the app
   □ Paper map
   □ Keeping track of the direction (north, south, east, or west)
   □ Surrounding landmarks (buildings, sculptures, landscape)
   □ Street signs/names
   □ Building signs/names
   □ Asking other people
   □ Other, please specify

On this page, please draw a map that shows your impression of the Texas A&M main campus <u>after conducting the wayfinding task</u>, with where we stand (the Rudder Plaza) as the center. Every map will be analyzed separately, so please do not omit features that you have already included in your previous map.

Rudder Plaza

Figure A.4: Post-Questionnaire

APPENDIX: B – TRIAL STUDY QUESTIONNAIRE RESULTS

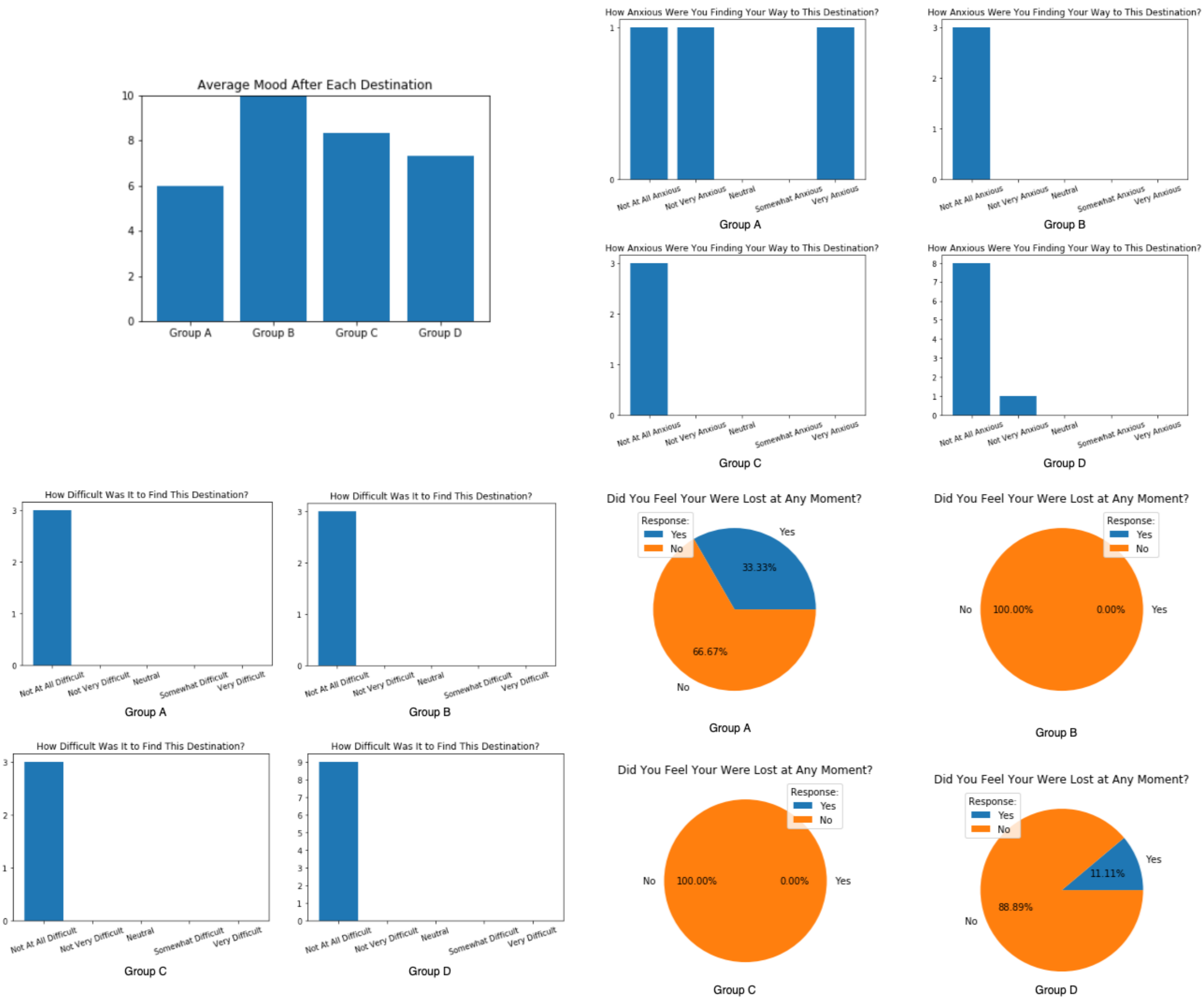

Figure B.1: Mid-Questionnaire Testing Results