An Intelligent Campus Lost-and-Found System Using QR-Based Tagging and AI-Driven Multimodal Matching

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ABSTRACT

The issue of lost items is a widespread occurrence in educational institutions, workplaces, and public environments, where the manual tracking and management of items is prone to inefficiencies. This study presents a web-based Lost and Found Tracking System intended to provide an online platform for reporting lost items and searching found property. The described system aims to allow individuals to submit reports containing item-specific data, such as categories, descriptions, locations, dates and accompanying imagery, as well as provide administrative tools to maintain and manage submissions. The system further implements an intelligent item-matching procedure that seeks to identify connections between lost and found items by analyzing textual and visual data. By facilitating standardized report storage and management as well as implementing a heuristic item similarity assessment, the system aims to reduce the cognitive load of finding lost property. The described system was further tested in terms of functional requirements and overall performance in order to evaluate its ability to effectively collect and store item-specific data and reports, as well as match found and lost items. The proposed system serves as a basis for developing an online tracking system Lost and Found items in an educational environment.

Keywords— Lost and Found System, Item Tracking, Web-Based Application, Intelligent Matching, Information Retrieval, Artificial Intelligence.

INTRODUCTION

The loss of mobile phones, wallets, identity cards, documents, electronic devices and other valuable items is a common event in schools, businesses, transport and other places. The recovery of such items usually depends on manual processes, such as notice boards, verbal communication, social media groups, messaging applications, or maintaining records manually. While these approaches may be effective for small communities, they become challenging as the number of users and reports grow.

One of the most common issues with current solutions is the lack of a centralized place to hold information about lost items and organize communication between reporters. People may report lost items in different channels, while finders may not be aware of the appropriate place to check. This problem results in relevant information being fragmented and sometimes hard to find when an item is discovered. At the same time, comparing descriptions of lost and found items requires much time and may miss similarities.

Modern web-based information systems can address many of these issues by acting as a central repository for all lost and found item reports and providing search and filtering tools. First, such a system would allow users to store any relevant data about a lost item, such as its type, description, date and location of loss, pictures and other information. Moreover, the system would allow users to search for reports using keywords and sort them according to various criteria.

Second, computer vision and natural language processing technologies can help match similar reports by analyzing the descriptions, types, locations, dates and other data of lost and found items in reports. Intelligent algorithms can suggest possible matches between a report about a lost item and any other reports about found items.

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The described issues with existing solutions and the outlined opportunities for improvement will be addressed by designing an intelligent Lost and Found Tracking System. The system will be based on a web platform and will offer users a centralized place to report lost items, search for them and manage found items. It will be possible to add new reports, view and edit existing ones, search for reports using keywords and sort them according to various criteria. The system will also have an item-matching algorithm that uses the data in reports to find possible matches between lost and found items.

The work's main contribution is the combination of centralized lost and found management and the intelligent matching of items in one system. The system aims to reduce the efforts spent on the manual search and comparison of items, optimize the storage of the relevant information, and help establish the contact between the owners and the finders. Such a system would be useful in a limited environment, such as in a university, college, or office, where a centralized lost and found system is required.

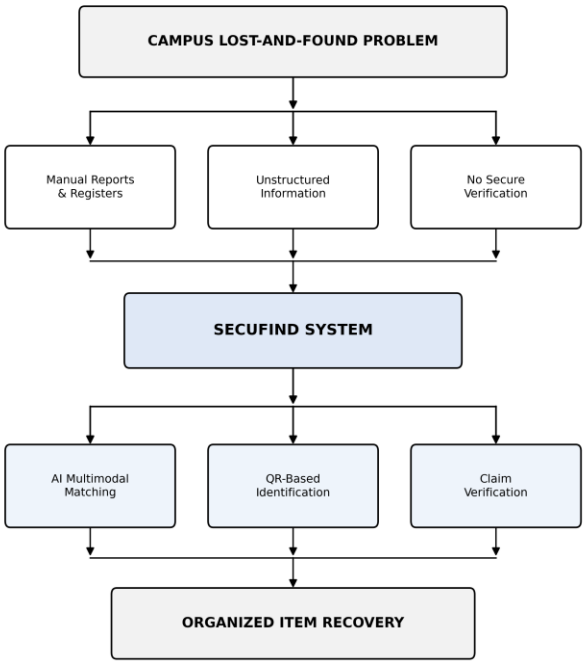

Fig. 1. Conceptual overview of the campus lost-and-found problem and the proposed SecuFind solution.

LITERATURE REVIEW

Traditional lost-and-found management in universities and other institutions typically involves reporting, notice boards, messaging groups and informal communication. These practices make lost-and-found challenging to maintain records and to link lost-item reports with matching found-item reports. Recent web-based systems have sought to address these issues by providing tools for reporting, searching, claiming and managing lost items [1]. These systems demonstrate that the shift of lost-and-found work to a structured digital platform can be effective but the basic systems still involve users to perform a manual search through the records. Artificial intelligence has created opportunities to automate the matching process. SmartFind for example combines image-based and text-based similarity to retrieve lost items in college and office settings [2]. Other research has explored the use of AI-powered lost-and-found platforms that combine image recognition with a web-based application framework [7]. Recently LostNet presented a dedicated lost-and-found image recognition framework which includes MobileNetV2, the Convolutional Block Attention Module (CBAM) and perceptual hashing [8]. This study demonstrates that acquired visual matching can be applied directly to the task of lost-and-found instead of being restricted to normal image-classification tasks. Recent research has turned to multimodal retrieval rather than using just one image or text description. A 2025 study proposed a design that combines YOLO a large language model and CLIP for intelligent lost-and-found retrieval. This design uses object detection to identify parts of an image, language processing to refine descriptions and CLIP to perform cross-modal matching [9]. Another recent system combined retrieval and

security monitoring by integrating uncertainty-aware retrieval CLIP-based semantic re-ranking multimodal validation and behavioral monitoring [10]. These advancements point towards a focus on lost-and-found systems which can operate with varied forms of data rather than relying on keyword searches. Image retrieval is crucial to these systems as photographs can provide a wealth of information that's difficult to convey with keywords. DeepFashion demonstrated how learned visual representations can be helpful to recognition and retrieval of similar items [3]. Studies on convolutional features also explored the potential of using pretrained CNN models as image-retrieval descriptors proving how visual representations learned can be effective without needing to train a complete retrieval model from scratch [4]. A larger survey on instance retrieval highlights how the field has moved from local descriptors like SIFT to CNN-based representations for visual retrieval [15]. Many established deep-learning models contribute to the foundation for extracting visual features. Very Deep Convolutional Networks (VGG) demonstrated that by increasing the depth of CNNs through the use of filters can lead to the creation of powerful visual representations [21]. ResNet added learning to enable networks to be significantly deeper and easier to train [16]. In situations where computing power is limited MobileNetV2 offers an efficient design that makes use of inverted residuals and linear bottlenecks [17]. These models are integral to SecuFind as a campus system may need to manage uploaded images without requiring expensive computing resources.

Attention mechanisms offer another way to boost representations. CBAM added an attention module that handles channel and spatial data separately and can fit into CNN models [18]. This is especially useful for lost-item images since the key parts of an object might take up a small spot in a photo. Object-detection methods can also pull out the parts from complex backgrounds. YOLO created an object-detection system that can find object positions and class chances straight from an image [19]. These ideas could be added to future SecuFind releases so the system first spots the right object area before looking for matches.

Another important research path is -modal image-text retrieval. Kaur and colleagues reviewed -modal information retrieval and stressed how vital it is to learn links between different kinds of data especially images and text [12]. These methods help lost-and-found work because one person may describe an item with words while another only gives a picture. CLIP tackled this issue by learning representations together with natural language guidance so text ideas can match images [5]. CLIP is therefore a choice, for systems where the query and stored item data may come in different formats.

Describing an item by colour, brand, shape, model or special marks is just as important as any detail. BERT showed that bidirectional Transformer representations can capture context from text and can be applied to natural-language tasks [20]. Sentence-BERT built on BERT to create sentence embeddings that can be compared quickly with cosine similarity making sentence representations useful for SecuFind when two users describe the same object with different words instead of identical keywords.

When the number of lost-and-found records grows efficient similarity search becomes crucial. Product Quantization offers a way to represent vectors with compact codes enabling approximate nearest-neighbor search [25]. Hierarchical Navigable Small World (HNSW) graphs give another method for retrieving approximate nearest neighbours in high-dimensional spaces [24]. FAISS supplies tools for similarity search and clustering of dense vectors and studies have explored GPU-based similarity-search techniques for very large collections of high-dimensional representations [22] [23]. These methods suggest that a future large-scale SecuFind could use vector indexing of matching every new report against every stored item.

Security is important as finding a match does not prove ownership. QR-based identification can connect an item with its digital record but QR codes also introduce security concerns. Literature on QR-code security investigated cryptographic techniques and the trade-off between security and easy scanning [26]. Broader QR-code application research uncovered security and privacy weaknesses in barcode-scanning apps. Discussed safeguards included URL checking and cryptographic protection [27]. The findings indicate that SecuFind must involve QR identification with privacy and claim-verification steps rather than QR alone being proof of ownership.

In general, the literature reveals a trend from manually managed lost-and-found services to systems using central databases, visual and text similarity, multimodal learning and automatic identification.

Existing works demonstrate capabilities such as web-based management [1] AI-based image and text matching [2] dedicated lost-and-found image retrieval [8] cross-modal retrieval [12] deep visual representations [15]-[18] semantic text representations [6] and secure QR identification [26] [27]. These tools are typically addressed separately or in separate contexts. SecuFind therefore unifies multimodal matching, QR item identification, central reporting and claim verification in one campus-focused framework. The aim is to use image, text, location and time data to rank matches while preserving a separate verification step to establish ownership.

PROPOSED METHODOLOGY

SecuFind is an intelligent lost-and-found service for the campus which integrates traditional methods of reporting lost items with the use of artificial intelligence, QR code identification, and verification of claims. The primary aim of the proposed approach is to decrease the reliance on manual searches and to enhance the probability of recovering lost items by making use of the data from a number of different sources.

A conventional lost-and-found system has users primarily rely on textual descriptions in order to carry out their searches, whereas SecuFind takes into account the image, the textual description, the location, and the time connected with an item. For items which have been previously registered, the system also includes a QR-code based method of identification. The entire methodology is made up of five main stages: data collection and reporting, feature extraction, multimodal matching, QR-based identification, and claim verification.

The system architecture as a whole includes a client side built with React, a backend developed using Spring Boot, a MySQL database, and a separate AI service written in Python. The backend functions as the main channel of communication between the user interface, the database, the AI service, the QR services, and the notification services.

System Architecture

The system is based on a modular architecture with each of the various responsibilities being managed by individual components. Users access the application via the web interface, whilst the Spring Boot backend looks after authentication, item reports, claims, QR operations, and notifications.

Item information and user records are kept in the MySQL database, and the AI service is implemented on its own so that image and text processing can be carried out separately from the main application.

The major components of the proposed architecture are:

- **User Interface:** Provides interfaces for reporting lost and found items, viewing possible matches, initiating claims, and interacting with QR-based recovery.
- **Application Server:** The Spring Boot backend manages REST APIs, authentication, user requests, item records, claims, and communication with the AI service.
- **Database Layer:** MySQL stores users, item reports, item descriptions, locations, timestamps, claims, verification information, and recovery status.
- **AI Matching Service:** A Python-based service processes images and textual descriptions and generates similarity scores.
- **QR Service:** Generates unique QR codes for registered items and handles QR scanning requests.

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- **Notification Service:** Sends notifications when a possible match is identified or when a QR code associated with an item is scanned.

- **Administrative Dashboard:** Allows authorized campus personnel to monitor reports, verify claims, and manage recovered items.

The technology choices and division of components follow the system specification provided for SecuFind.

Table I: Item Information Attributes

Attribute	Description
Item ID	Unique identifier assigned by the system
Category	Type of item such as bag, laptop, bottle, etc.
Description	Textual description of the item
Image	Photograph uploaded by the user
Location	Place where the item was lost or found
Date/Time	Time associated with the report
User ID	User associated with the report
Status	Lost, Found, Claimed, or Resolved
Verification Data	Information used for claim verification

Table I above contains key attributes used to store and manage lost-and-found item information in the proposed SecuFind database. This table contains such attributes as ID, category, description, image, location, date/time, user information, status, and verification data. All of these categories contribute to the report's enhanced organization and facilitate the faster matching of found and lost items and establishing secure and verified ownership.

AI-Based Multimodal Matching

The system uses both image and text data to identify matches; when an image is uploaded it is converted into a feature representation by means of a CNN-based model or a CLIP-based model, and the text description is processed using TF-IDF with cosine similarity or sentence embeddings.

The location and time are considered as well since they provide context in cases where several items appear to be similar or have similar descriptions. Each of these inputs—image, text, location and time—receives a score according to how well it matches the target, and the scores are then combined by means of weights to obtain a matching score.

The formula for the score is:

$$S_{\text{final}} = w_i \times S_{\text{image}} + w_t \times S_{\text{text}} + w_l \times S_{\text{location}} + w_r \times S_{\text{time}} \quad (1)$$

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The similarity scores for the image, the text, the location and the time are denoted by Simage, Stext, Slocation and Stime respectively, and the weights wi, wt, wl and wτ indicate the degree of importance assigned to each factor in the decision.

QR-Based Item Identification

SecuFind offers a proactive recovery solution based on QR codes. In particular, a user may register an item in advance and encode the information in a QR code that is attached to the item. Once the item is found by another person, they are able to simply read the QR code and inform its registered owner skipping the whole AI matching stage. Therefore, QR identification codes may be used to directly recover the specific items registered by users, while the AI matching system is applied to items without any specific identification codes.

Claim Verification

In turn, any match found by the system is not necessarily true, and there is always a possibility of a false match. That is why an additional step of claim verification is required before the found item is transferred to the new owner. In particular, to verify ownership claims, the system may ask to answer specific verification questions that are set during the registration step. It allows ensuring that the item's owner who claims to own the lost item has indeed lost it and not claiming someone else's belongings. In particular, if a claim verification fails, an unverified claim needs to be reviewed manually by an admin.

Notification and Administration

After that, the system may notify users about the outcome of the claim verification, or the administration may update the status of the claim and the item itself in case of a successful match. In particular, an admin dashboard may offer statistical information about the number of found items, their categories, and items that have been successfully recovered.

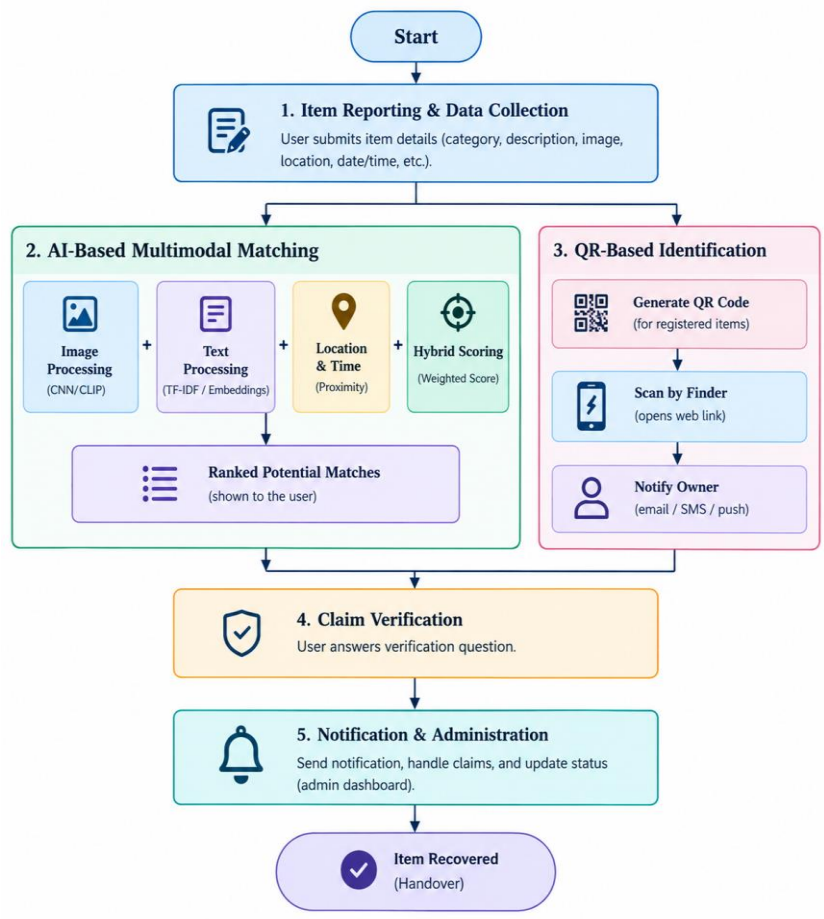

Fig.2. Work Flow of System

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Fig.2 shows the entire workflow of the proposed SecuFind system. Item reporting and data collection first, then AI-based multimodal matching with image, text, location and time information. QR-based identification provides an additional retrieval mechanism. Claim verification ensures safe ownership before notifications and handover of recovered items.

RESULTS

SecuFind system allows you to report, locate, identify and recover lost items on the school campus. This system incorporates item reporting, matching, QR-codes, claiming checks, alerts and administration functions in one system.

The item reporting function allows you to enter all the relevant information of a lost or found item. The report will require category, description, photo, location, date and time of finding. All the reports will be stored in the database for future matching and identification.

The second function of the system is matching. It scans the photo of the lost item and compares it to the similar images in the database. The system matches the description and photo of the found item to the reports in the database. Furthermore, the system analyzes the location and time of finding and provides the most relevant results. All the checked details are given a score based on the probability of the match. In addition, the system implements QR-codes and claiming function. A specific QR-code can be attached to the lost item when an owner registers it in the system. A finder can scan the code with a QR reader and get the information on the item. Then, the system asks for the verification of the claimant.

Finally, after the most relevant offers have been picked by a matchmaker algorithm, SecuFind system suggests that the claimant goes through the verification. SecuFind realizes that a match is not always correct, which is why a claimant needs to provide additional documents for verification. If a document is not provided or if it does not match an item description, the case is sent to the administrators for a decision.

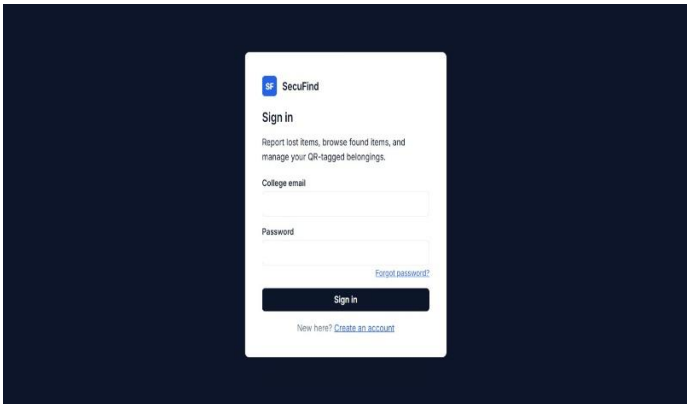

Fig.3. Sign-In Page

Fig 3 Provides secure access to the SecuFind interface using the registered college email and password.

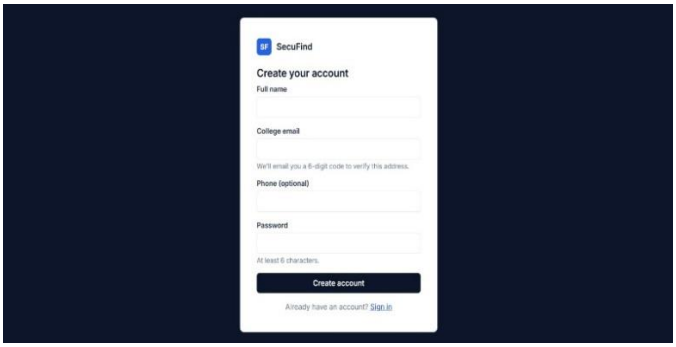

Fig.4. Account Registration Page

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Fig 4 Allows a new user to create an account by providing basic information and credentials.

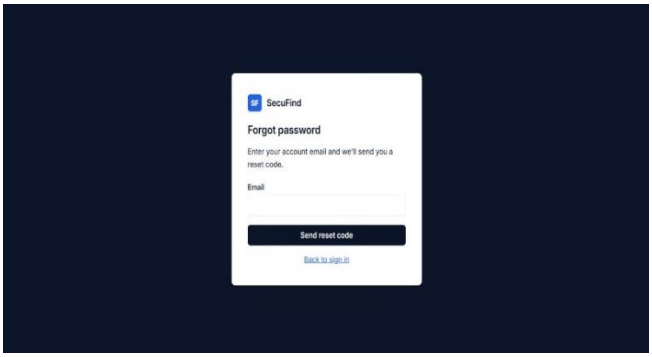

Fig.5. Password Recovery Page

Fig 5 Enables a user to request a code to recover their lost account access.

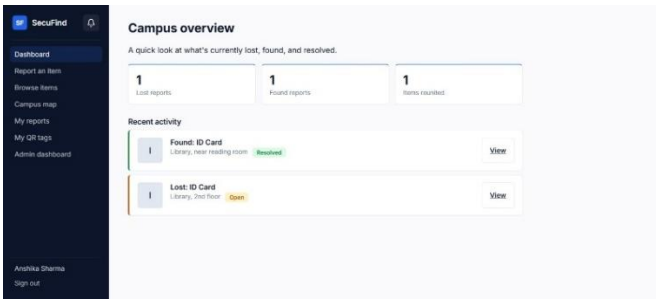

Fig.6. Campus Overview Dashboard

Fig 6 Shows reported lost and found items and recent campus activity.

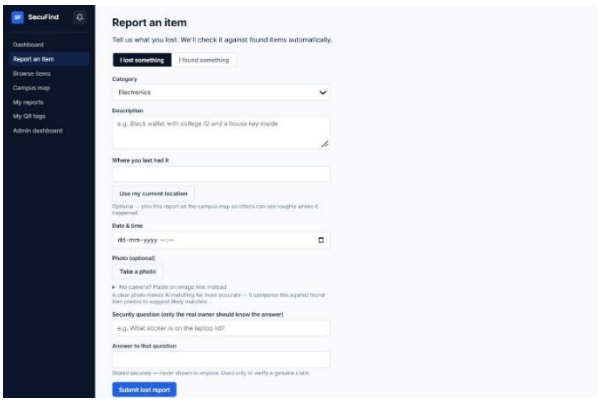

Fig.7. Lost Item Reporting Page

Fig 7 Enables a user to submit details, location, time, image, and verification information of a lost item.

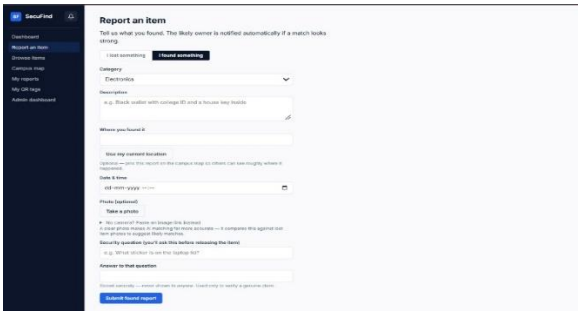

Fig.8. Found Item Reporting Page

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Fig 8 Enables a user to report a found item and provide information needed to identify its owner.

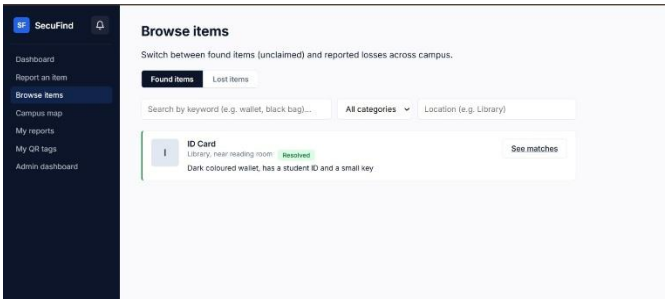

Fig.9. Browse Items Page

Fig 9 Provides a searchable database of all reported found and lost items with filtering options.



Fig.10. Campus Map

Fig 10 Shows the approximate location of all found items on an interactive campus map.

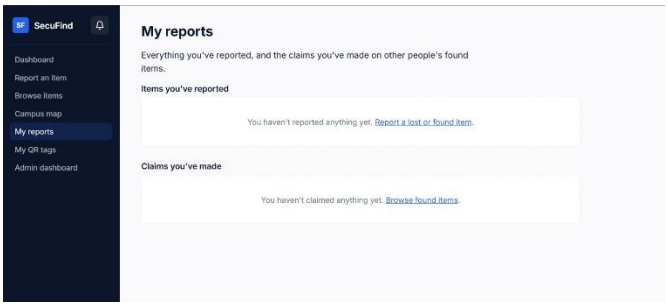

Fig.11. Report Dashboard

Fig 11 Enables a user to view submitted item reports and track their claims.

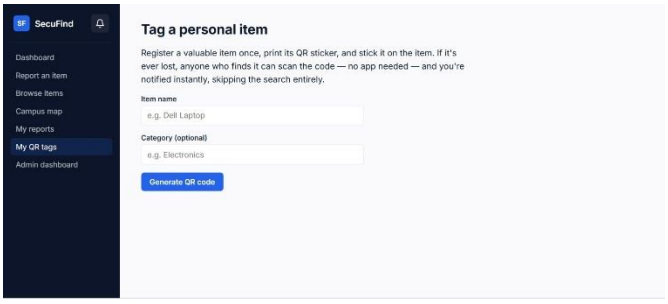

Fig.12. Personal Item QR Tagging

Fig 12 Enables a user to register personal belongings and generates QR codes for identifying and reporting lost items.

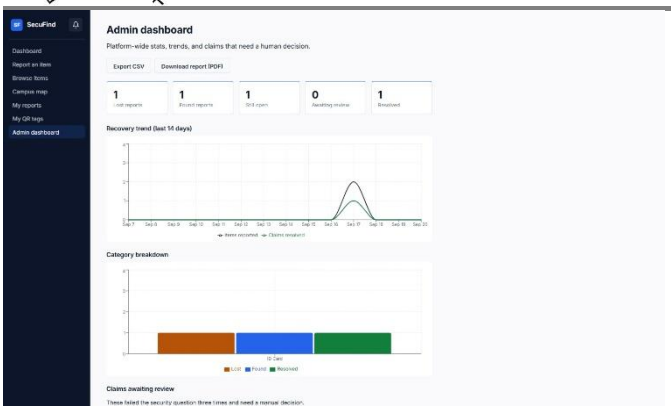

Fig.13. Admin Dashboard

Fig 13 Provides the administrator with statistics, recovery trends, category information, and tools to manage reported items.

DISCUSSION

In our opinion, the outcome proved that using identity methods can lead to a more efficient and integrated campus lost-and-found ecosystem. Unlike traditional solutions, which are mostly record- and communication-based, SecuFind prioritizes the consolidation of relevant information and the use of automated cross-referencing of lost and found reports.

We think that using multimodal information is also a great advantage because descriptions or images of items may not be specific enough on their own, but combined, they create a more detailed overview of the object. Also, We believe that the inclusion of location and time helps to characterize the lost item and distinguish between similar reports.

We think that using both text-to-image, image-to-text, image-to-image, and text-to-text similarity is a better option compared to using just one type of comparison.

Using QR codes as a form of identifying objects that were reported as lost seems like a flexible solution to distinguish between items. While the AI-powered similarity detection helps to find comparable lost-and-found reports, QR codes can be used to identify reported lost items.

We think that the verification step helps to make sure that the person who reported finding an item is not lying about ownership, and We believe that the system's ability to ask additional verification questions prevents ownership fraud.

We believe the system's design allows for independent updates to the front and back ends, as well as the database and AI. However, there is still a need to observe how well the suggested solution would function in the described setting. We think that the following experiments should measure precision, recall, and F1 score, Top-K accuracy, speed, and recovery rate.

Overall, We think that the proposed solution, with its advanced multimodal similarity detection, QR code usage, and verification system, has the potential to be an efficient lost-and-found system for a campus but requires practical validation.

CONCLUSION

This paper presents SecuFind, an innovative campus item recovery system, which utilizes QR-based identification, AI-driven multimodal matching, and secure claim verification to optimize the conventional lost-and-found process. The solution tackles the shortcomings of the existing practice, which includes unorganized

reporting, challenges in identifying potential owners, lack of a reliable verification mechanism, and delayed communication between stakeholders.

The AI component enables effective identification through image and text recognition while considering additional attributes, such as the location and time of discovery. The former two factors, in particular visual characteristics of items and textual descriptions, were selected due to their ability to improve the accuracy of multimodal matching on both the item and text sides. Meanwhile, the inclusion of location and time was motivated by the need to enable contextual identification and ensure the relevance of item matches. This approach also involves computing scores based on the identified attributes and combining them to determine the degree of similarity between items in terms of multimodal matching.

In turn, the QR component facilitates scanning items to identify their owners by relying on previous submissions of items with matching descriptions. In this respect, the QR-based identification was integrated into the system to capitalize on its strengths in recognizing objects with specific attributes. Combined with the aforementioned AI-based multimodal matching, the QR component allows the system to be used not only for identifying claimed items via their descriptions but also for retrieving voluntarily submitted items. Another key design consideration was the need to ensure security during the verification process, which was addressed by implementing a special verification procedure to prevent mismatches and ensure that items are only claimed by their owners.

The solution's design incorporates a web interface, backend developed with Spring Boot framework, database, and AI service, which together address the requirements of flexibility and scalability. These factors were determined by the need to implement a working proof of concept with the ability to demonstrate the effectiveness of the system in terms of increased discoverability and accuracy of item identification within the local campus community. In terms of future development, the system could benefit from implementing a more sophisticated scoring mechanism, which would rely on multiple factors. The design could also be expanded to include multilingual support, more advanced scanning procedures, and enhanced processing of suspicious claims.

Overall, the proposed solution represents an innovative approach to optimizing the conventional lost-and-found practice by offering an organized, automated, and accurate item identification and verification process. By capitalizing on the ability of AI to implement effective multimodal matching, QR recognition, and implementing a special verification procedure, SecuFind creates opportunities to operate as a reliable service for item recovery in the local campus community.

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