

Blockchain and AI-Based Platform for Managing Lost and Found Items in Public Places

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Every day, innumerable items are lost and unclaimed in shopping malls, restaurants, airports, and other public places. While some lost and found systems exist, they are often non-automated, poorly structured, and vulnerable to data loss. We present a blockchain- and AI-based platform that integrates Internet of Things (IoT) for real-time tracking and zero-knowledge proofs (ZKPs) for privacy-preserving verification. In this platform, users can report lost or found items, for which information hashes are generated and then stored on the blockchain to ensure immutability, transparency, and trust. Artificial intelligence is used to compare lost items with potential found items to reduce the complexity of searching. To evaluate the AI component, we used a transfer learning technique with pre-trained CNN models, namely ResNet50, VGG16, and MobileNetV3, on the Caltech-256 dataset filtered to 10 relevant classes (1,219 images), attaining 95.46% \pm 1.09% accuracy in 5-fold cross-validation for ResNet50 without augmentation, 93.99% \pm 3.44% on holdout test, and 94.54% \pm 3.29% under Gaussian blur for robustness. Feature embeddings yielded top-1 matching accuracy of 89.01% and top-5 of 95.60%, outperforming recent image-matching baselines in noisy real-world conditions while maintaining sub-0.0003 s inference time. These results establish a scalable, trustworthy global ecosystem for lost-and-found management.

Keywords: Blockchain; Artificial Intelligence; Lost and Found Management; Privacy Preservation; IoT Integration



Introduction:

Nowadays, the loss of personal items in public places is a common incident. These incidents not only cause financial loss but also cause emotional distress for individuals because lost items often include essentials like purses, phones, or other sentimental valuables. The existing traditional search services are usually manual or semi-digital, depending on paper logs, isolated databases, or basic online systems managed by individual institutions. Such systems are affected by inefficiencies, such as reports being misplaced, data being altered inadvertently or maliciously, and a lack of cross-institutional coordination, which can cause frustration for users. Furthermore, in a globalized society where the travelling of people between cities and countries is increasing, the lack of a standardized platform aggravates these challenges, which results in lower recovery rates for lost items.

Management of lost and found items in public places remains a persistent challenge because of the unreliable nature of existing lost and found systems. In many cases, these lost and found systems are confined to specific areas like a single airport or university campus without any mechanism for interoperability. For instance, if a person forgets a bag on a bus and it ends up at a train station, there is no straightforward way to connect the dots across these silos. This isolation leads to duplicate efforts as finders might report items to one authority while owners search another, resulting in missed opportunities for reunions. Users cannot easily search for their items across different locations and get instant notifications if a match is found between a lost or found item. Instead, they have to physically visit offices that manage lost and found items or call helplines, which is inconvenient and time-consuming. Recent research has explored AI for image-based and multimodal matching of lost items [1]. However, it remains limited to single institutions, relies on centralized databases vulnerable to breaches, or lacks full integration of intelligent matching with decentralized trust mechanisms.

Lack of trust and verification is another issue, as manual systems usually have handwritten logs or spreadsheets, which are vulnerable to human error or even deliberate tampering. In crowded places like shopping malls, staff may overlook reports due to daily chaos, and items may be claimed fraudulently without proper checks. Digital alternatives are better but still depend on centralized servers that can be hacked or manipulated, as evidenced by numerous data breaches in institutional databases over the years [2]. Privacy concerns further complicate matters as people hesitate to share their personal details in reports because of fear of misuse of their details, yet anonymity can hinder effective communication between owners and finders [3]. In these situations, there is a need to shift toward a decentralized, secure, and intelligent system that ensures data integrity, transparency, and facilitates cross-platform collaboration.

Blockchain is a distributed ledger in which recorded transactions are immutable, decentralized, and verifiable by all participants [4]. Each block in the chain contains data hashed using cryptographic techniques, ensuring that once information is added, it cannot be retroactively changed without consensus from the network [5]. The intrinsic security of blockchain makes it ideal for scenarios where trust is required in the absence of a central authority. Smart contracts are self-executing code that automates processes based on predefined conditions, which help blockchain to optimize operations like item matching and user notifications [6]. Artificial intelligence integration further enhances blockchain's capabilities. Artificial intelligence methods, particularly in the areas of natural language processing and computer vision, can analyze lost or found item descriptions, images, and metadata to suggest matches between lost or found items. The combined use of blockchain and AI is not only helpful in data integrity but also helps in intelligent automation, which makes the system more user-friendly and effective.

This paper presents a platform in which users can post lost or found items. Then, hashes of this information are generated and stored on the blockchain through a smart

contract for secure data storage, and artificial intelligence is used to identify possible matches between lost and found items, aiming to revolutionize lost and found management. By decentralizing the process, we eliminate single points of failure and promote inclusivity across public spaces.

Literature Review:

This literature review consolidates existing research on lost and found systems, blockchain applications in trust-sensitive domains, and AI-driven matching technologies, emphasizing complementarities and gaps in incorporating these for public space management. It pinpoints opportunities for decentralization to overcome silos in conventional systems and utilizes AI for proactive intelligence, establishing the foundation for the proposed hybrid platform. The review is organized into subsections addressing traditional systems, blockchain in related domains, AI in matching, IoT tracking, and Privacy-Preserving Mechanisms.

Existing Lost and Found Systems:

Historically, lost-and-found operations in urban transportation hubs have depended mostly on manual procedures like paper logbooks and limited online reporting. Some integration of digital tools has occurred, yet these systems continue to face low recovery efficiency for personal items. For instance, industry sources indicate that a substantial portion of lost passenger belongings in public transport remains unclaimed [7]. Digital tracking platforms have improved baggage recovery in the aviation sector, but mishandling still prevails. According to SITA's Baggage IT Insights, the mishandling rate in 2022 was 7.6 bags per 1000 passengers, and only a minority of approximately 7% of mishandled bags were classified as permanently lost or stolen [8]. Even in such digitized environments, these systems often lack comprehensive matching capabilities and remain centralized. More recent digital platforms (e.g., LostNet [9]) have improved retrieval but still lack decentralized trust and cross-platform interoperability.

Blockchain Applications in Related Domains:

Blockchain has transformed high-security sectors, including healthcare, where blockchain-based decentralized applications are evaluated using performance and security metrics [10]. Voting systems use smart contracts for verifiable anonymity, a concept adaptable to anonymous item claims [11]. Supply chain traceability assures end-to-end visibility, paralleling the need for tracking lost items from report to return [12]. Additional works accentuate blockchain's role in reducing fraud through consensus mechanisms [13]. In IoT contexts, blockchain integrates with devices for secure data exchange, hinting at future integrations with smart tags for items [6][14]. Overviews of blockchain architecture and trends further support its applicability [5]. Cybersecurity vulnerabilities and countermeasures are also critical considerations [2]. Decentralizing privacy using blockchain protects personal data, which is relevant for user reports [3].

AI Integration in Matching and Search:

Artificial Intelligence (AI) has transformed searching and matching functionalities in digital platforms. NLP techniques are used for semantic matching of descriptions [15]. Computer vision is used for comparisons of images [16]. The integration of both NLP and computer vision has led to multimodal matching systems, where both textual and visual information are jointly analyzed to improve retrieval precision.

IoT and Real-Time Tracking:

The Internet of Things (IoT) is growing to enable real-time geolocation and condition monitoring of physical assets. In a smart city, IoT-based asset management systems have helped in the reduction of loss, theft, and misplacement incidents through proactive alerts and rapid recovery mechanisms. Despite these advances, standalone IoT tracking systems remain vulnerable to data tampering, single points of failure, and a lack of trust in centralized intermediaries. Our approach combines IoT data with blockchain to ensure immutable

recording of IoT-generated events (e.g., location timestamps, custody transfers), thereby enhancing transparency, auditability, and resistance to fraud [17]. Integration of IoT with blockchain has been explored for secure asset tracking in smart cities and supply chains, providing immutable logs of location data [18].

Privacy-Preserving Mechanisms:

Zero-Knowledge Proofs (ZKPs) enable a prover to convince a verifier of the truth of a statement without revealing any information beyond the statement's validity [19]. In this work, we employ ZKPs to allow privacy-preserving verification of user claims (e.g., ownership of a reported item) without disclosing sensitive personal information.

Methodology:

In the methodology of the proposed platform, we present the integration of advanced technologies like blockchain, AI, IoT, and zero-knowledge proofs (ZKPs) for the management of lost and found items. The core experimental focus of this study is on the AI component, while the other components (blockchain, IoT, and ZKP) are described at a conceptual level because they form the foundational infrastructure for deployment rather than experimental variables. This methodology outlines the System Overview, component interactions, and algorithmic strategies that are required for a full-scale implementation of the platform.

System Overview:

The proposed platform integrates Artificial Intelligence (AI), Blockchain, Internet of Things (IoT), and Zero-Knowledge Proofs (ZKPs) to provide a secure, transparent, and efficient solution for managing lost and found items in public spaces. Figure 1 illustrates the overall workflow of the system.

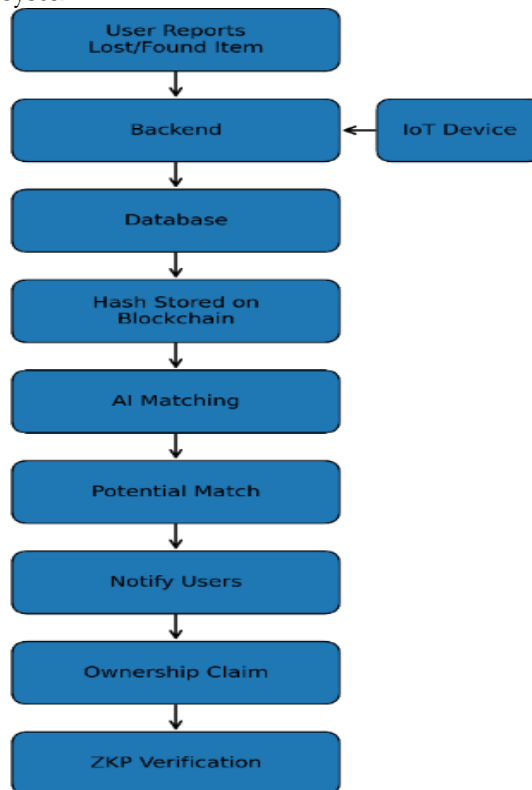


Figure 1. Flowchart of the system workflow, illustrating the interaction among its core components.

User Reporting:

The process begins when a user submits a report for a lost or found item through the interface of the platform. The user provides relevant information such as item description,

images, time and location of loss or discovery, and optionally an IoT tag identifier (if the item is equipped with a tracking device). This structured input ensures that sufficient data is available for accurate identification and matching in later stages.

Backend Processing and Data Storage:

Once the report is submitted, it is transmitted to the backend server, where the data is validated, formatted, and securely stored in a centralized database. If an IoT device is associated with the item, the backend also collects real-time or recent location data from the device. This step ensures data consistency and prepares the information for further processing.

Blockchain Hashing and Integrity Assurance:

To guarantee data integrity and prevent tampering, a cryptographic hash of the report is generated and stored on the blockchain via smart contracts. Instead of storing full data on-chain (to reduce cost and improve efficiency), only the hash and essential metadata are recorded. This enables later verification of data authenticity while maintaining scalability.

AI-Based Feature Extraction and Matching:

The AI module processes uploaded images and textual descriptions to extract distinguishing features such as shape, color, patterns, and semantic attributes. These features are compared against existing records in the database using similarity matching algorithms. This step significantly enhances the likelihood of identifying potential matches beyond simple keyword-based searches.

Potential Match Identification:

When the AI system detects similarities between lost and found item reports, it generates a list of potential matches ranked by confidence scores. Threshold values are applied to filter out low-probability matches, ensuring that only relevant candidates are considered for notification.

User Notification:

Once a potential match is identified, the system automatically notifies the corresponding users (both the reporter of the lost item and the finder). Notifications may include summarized details and similarity indicators, enabling users to review and confirm whether the match is valid.

Ownership Claim Process:

If users agree that a match is valid, the claimant initiates an ownership verification request. At this stage, the system requires proof of ownership, such as specific item attributes, purchase details, or other identifying information, without immediately exposing sensitive personal data.

Privacy-Preserving Verification using ZKPs:

To protect user privacy, the platform employs Zero-Knowledge Proof mechanisms that allow a user to prove ownership or specific attributes of an item without revealing the underlying sensitive information. This ensures that verification is both secure and privacy-preserving, reducing the risk of identity exposure or fraudulent claims.

IoT-Based Real-Time Tracking (if applicable):

For items equipped with IoT tags, real-time location updates are continuously integrated into the system. These updates can assist in narrowing down the item's location and improving match accuracy. The location data is securely logged and can also be hashed onto the blockchain to ensure tamper-proof tracking records.

Overall, the system combines AI-driven intelligence for accurate matching, blockchain technology for data integrity and transparency, IoT capabilities for real-time tracking, and ZKP-based mechanisms for privacy-preserving verification. This integrated workflow enhances trust, efficiency, and reliability in managing lost and found items in public environments.

Artificial Intelligence Module:

The artificial intelligence module of the proposed platform uses transfer learning in deep learning that leverages pre-trained models trained on large image datasets such as ImageNet. In this technique, we fine-tune an existing model for a particular task by keeping the pre-trained layers fixed and training only a new final layer for the target categories, instead of training a convolutional neural network (CNN) from scratch, which is costly and time-consuming. The following are the subsections in which the dataset, model architectures, training procedure, evaluation metrics, and feature-based matching approach employed in this study are described.

Dataset Selection and Preprocessing:

In this research, we use the Caltech-256 dataset because it is a well-established benchmark for object recognition with diverse, high-quality images, allowing controlled evaluation of transfer learning [20]. According to our lost and found scenario, we filtered this dataset to 10 relevant classes, i.e., backpack, CD, coffee mug, computer mouse, eyeglasses, headphones, iPod, laptop, umbrella, and watch. From all these classes, we obtained a total of 1,219 images. Data was stratified and split into 70% for training, 15% for validation, and 15% for testing. Transforms included resizing of images to 224x224, normalization, and augmentation (flips, rotations, jitter) for training; none for validation/test; Gaussian blur for robustness testing.

Models:

We fine-tuned three pre-trained models from Torch Vision:

ResNet50: A residual network having 50 layers. We replaced the final fully connected layer with one outputting 10 classes and froze earlier layers, optimizing only the classifier (2,048 input features).

VGG16: A convolutional network having 16 layers. It was also modified by replacing the last classifier layer (4,096 input features).

MobileNetV3: A lightweight model for mobile deployment, with the final classifier adjusted (960 input features).

By fine-tuning only the final layers, we reduced cost and time while maintaining strong feature extraction capabilities.

Training and Evaluation:

In training, the model was trained using cross-entropy loss, Adam optimizer with a learning rate of 0.001, 30 epochs with early stopping if validation loss did not improve for 5 epochs. 5-fold CV assessed generalization. Models were evaluated on accuracy, precision, recall, F1, macro AUC, inference time, with 95% confidence intervals. We extracted 2048D features from ResNet50 for matching, computed cosine similarities between lost/found subsets, evaluated top-1/5 accuracy, and intra/inter-class distributions.

Blockchain Module:

Blockchain technology is helpful for the management of data to ensure security, authenticity, and tamper-proof recording of lost and found transactions. The information of the report of lost or found items will be hashed by using cryptographic techniques, and then these hashes will be recorded on a block. We stored information hashes instead of actual information because storing actual information is costly. A smart contract automates the processes of verification, matching of lost or found items, and notification. Blockchain ensures that all actions are immutable and transparent to reduce fraudulent claims and ensure trust among the people.

Experimental Evaluation:

In this section, the experimental evaluation of the artificial intelligence component within the blockchain and AI platform for lost and found item management is presented. The evaluation carefully measures the overall performance of the models of deep learning in item

classification and similarity-based matching, with emphasis on generalization, robustness, and practical applicability. The experiment was conducted by using the filtered Caltech-256 subset. The principal aims were to benchmark classification accuracy under varied training conditions, assess model robustness against image degradation, and validate the effectiveness of feature embeddings for practical matching contexts.

Experimental Setup:

The experiment was conducted in Python using the PyTorch framework, along with torchvision for pre-trained models. The scikit-learn library is used for metrics computation. Matplotlib/Seaborn was used for visualization. The Caltech-256 dataset was filtered to 10 relevant classes, and then the data was stratified and split for training, validation, and testing. A batch size of 64 was used, Adam optimizer with learning rate 0.001, cross-entropy loss, and early stopping after 5 epochs of non-improving validation loss (maximum 30 epochs). The 5-fold stratified cross-validation was also employed to mitigate bias from limited sample size and provide reliable estimates of model performance. Models were trained both with and without data augmentation to isolate their contribution to generalization. A Gaussian blur transformation (kernel size 5, sigma range 0.1–2.0) was also applied to the test set to simulate real-world image imperfections like motion blur or low-quality user uploads. The test set was evenly divided into simulated "lost" (91 items) and "found" (92 items) subsets. 2048-dimensional feature embeddings were extracted using the penultimate layer of the final ResNet50 model, and cosine similarity was computed pairwise. All reported metrics include mean values with standard deviations or 95% confidence intervals where applicable.

Classification Performance via 5-Fold Cross-Validation:

The classification performance of three models, i.e., ResNet50, VGG16, and MobileNetV3, was evaluated under both augmented and non-augmented training regimes. Table 1 summarizes the macro-averaged results across five folds.

Table 1. 5-Fold Cross-Validation Performance Summary (Macro-Averaged)

Model	Augmentation	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Macro AUC
ResNet50	Yes	94.79 ± 1.69	94.69 ± 1.56	94.36 ± 1.67	94.32 ± 1.66	0.9984 ± 0.0007
ResNet50	No	95.46 ± 1.09	95.08 ± 0.98	95.05 ± 1.32	94.94 ± 1.17	0.9987 ± 0.0009
VGG16	Yes	94.69 ± 1.58	94.83 ± 1.32	94.25 ± 1.69	94.34 ± 1.56	0.9980 ± 0.0007
VGG16	No	94.50 ± 1.36	94.44 ± 1.36	94.10 ± 1.12	94.11 ± 1.25	0.9981 ± 0.0005
MobileNetV3	Yes	94.11 ± 0.94	93.87 ± 0.72	93.37 ± 1.41	93.39 ± 1.12	0.9977 ± 0.0005
MobileNetV3	No	93.44 ± 1.12	93.36 ± 0.92	92.68 ± 1.49	92.80 ± 1.24	0.9979 ± 0.0002

ResNet50 achieved the best performance consistently, with augmentation yielding marginally lower and less stable results compared to the non-augmented case, as shown in Figure 2. It shows that the dataset's inherent variability was sufficient for effective learning without heavy augmentation, though augmentation enhanced robustness in subsequent tests.

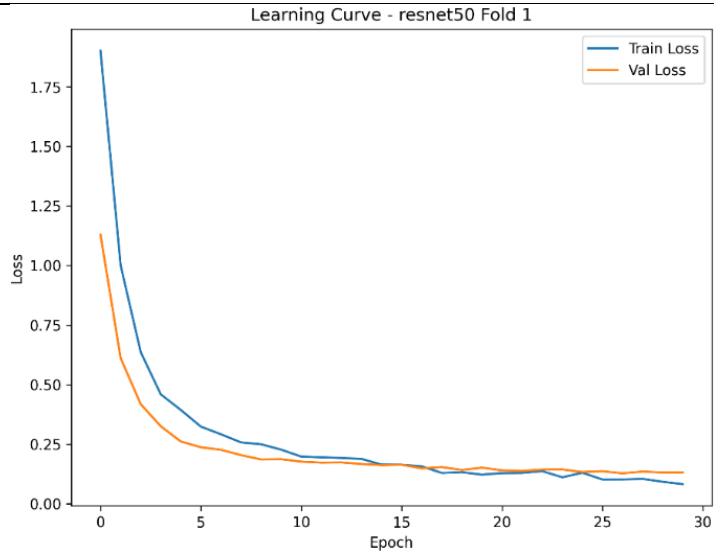


Figure 2. Learning curve (training and validation loss) for ResNet50 with data augmentation in Fold 1 of 5-fold cross-validation.

Per-fold breakdowns revealed the highest accuracies in folds with balanced validation distributions (e.g., 96.15% for ResNet50 augmented Fold 1), with occasional drops attributable to challenging class overlaps (e.g., iPod and headphones), as illustrated in Figure 3. The per-class performance metrics are presented in Figure 4, while ROC curves and AUC scores are shown in Figure 5.

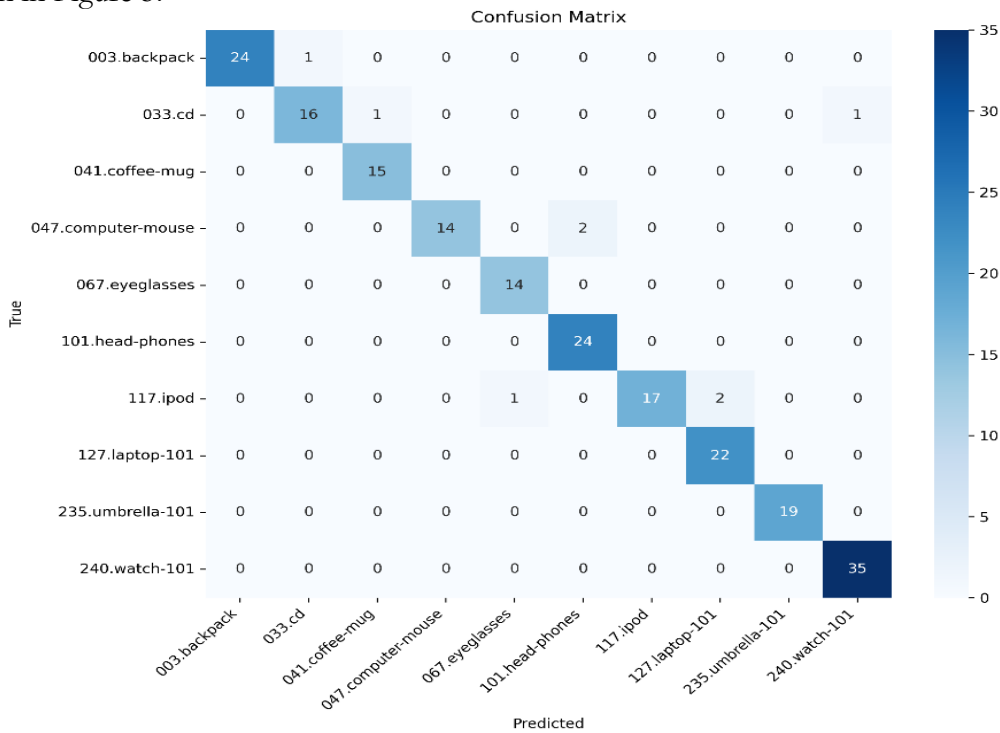


Figure 3. Confusion matrix of ResNet50 classification results on the validation set (Fold 1, with data augmentation).

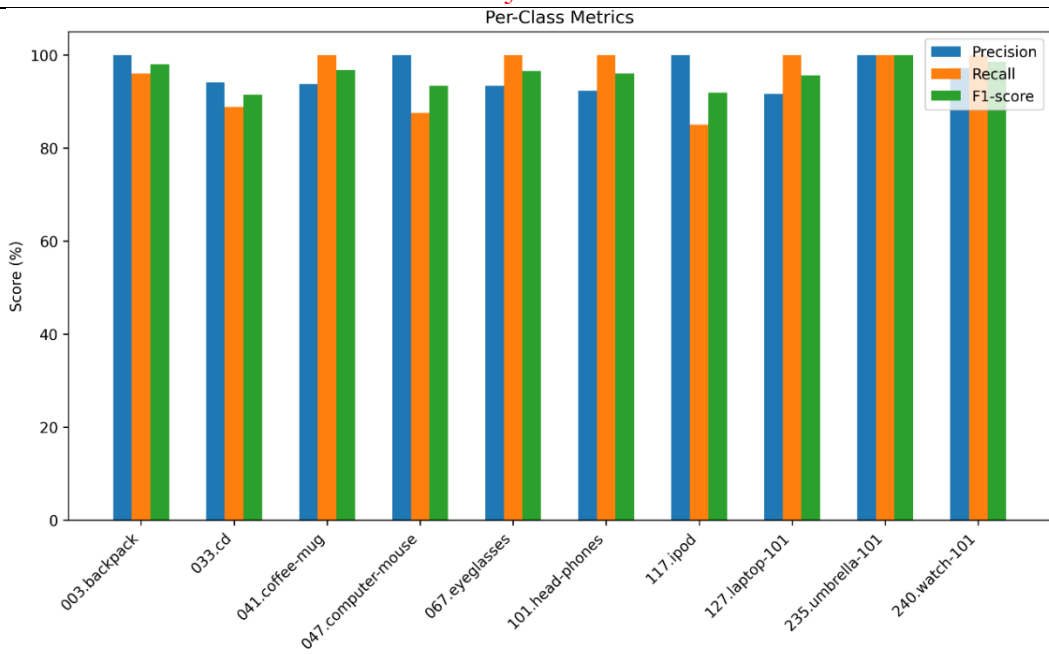


Figure 4. Per-class precision, recall, and F1-score for ResNet50 (Fold 1, augmented training).

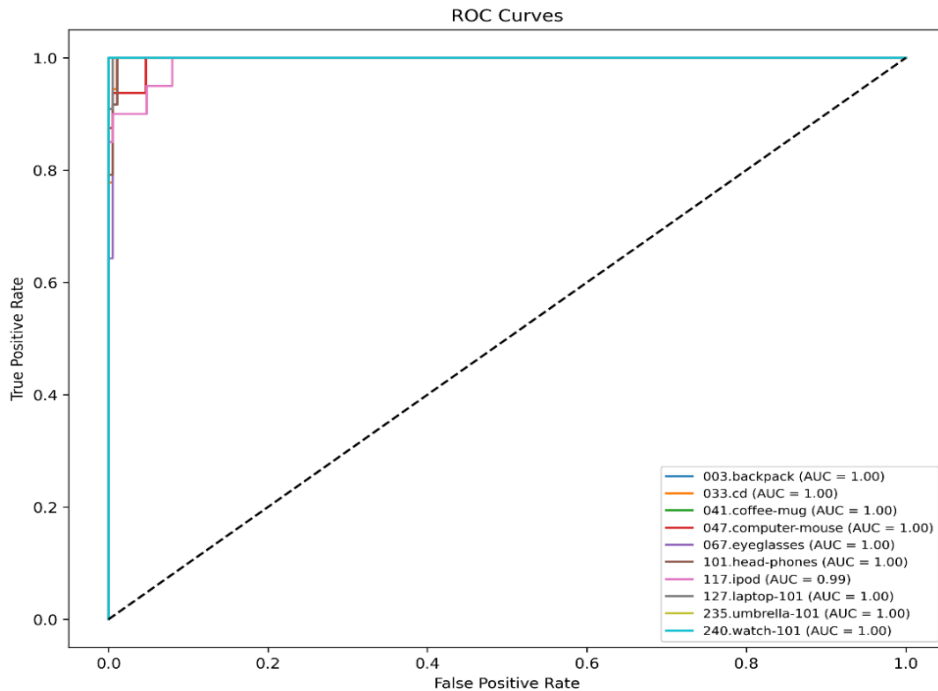


Figure 5. (ROC) curves and per-class AUC scores for ResNet50 with data augmentation – Fold 1 (5-fold cross-validation).

The inference times are approximately 0.0001 to 0.0003 seconds per image, which shows the suitability for real-time deployment.

Holdout Test and Noise Robustness Evaluation:

The top-performing setup of ResNet50 with augmentation was trained again by using the combined training and validation data and then evaluated on the unseen holdout test set. The results are provided in Table 2. The confusion matrix and class-wise performance for the holdout test set are shown in Figures 6 and 7.

Table 2. Holdout Test and Noise-Robustness Performance

Test Variant	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Macro AUC	Inference Time (s/image)
Standard Test	93.99 ± 3.44	93.86 ± 3.48	93.52 ± 3.57	93.54 ± 3.56	0.9952	0.0003
Noise (Gaussian Blur)	94.54 ± 3.29	94.64 ± 3.26	93.85 ± 3.48	93.95 ± 3.45	0.9941	0.0001

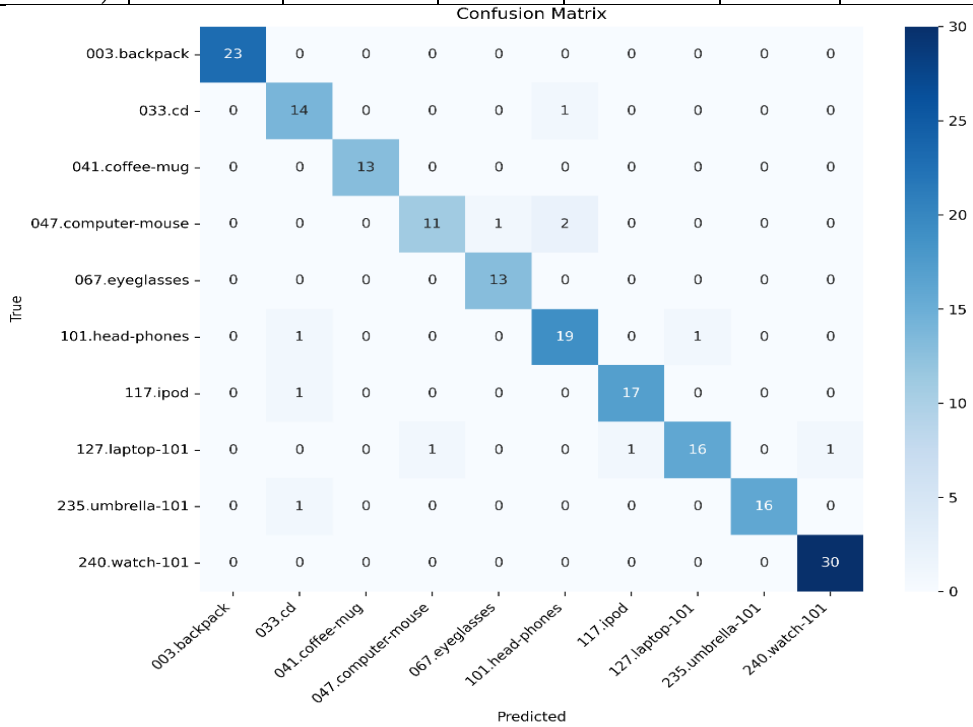


Figure 6. Confusion matrix for the final ResNet50 model on the holdout test set.

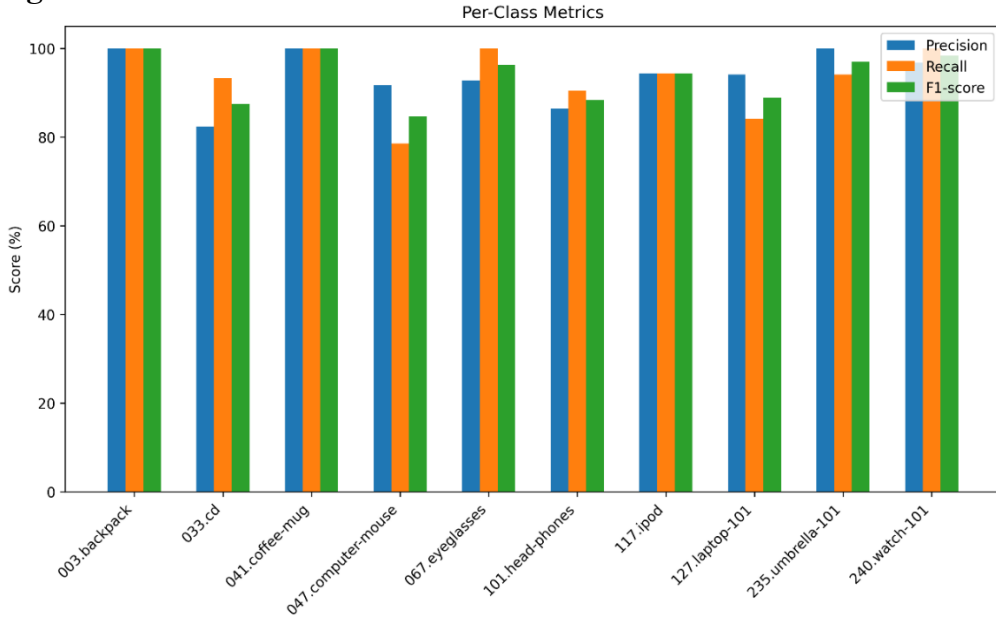


Figure 7. Per-class precision, recall, and F1-score for the final ResNet50 model on the holdout test set.

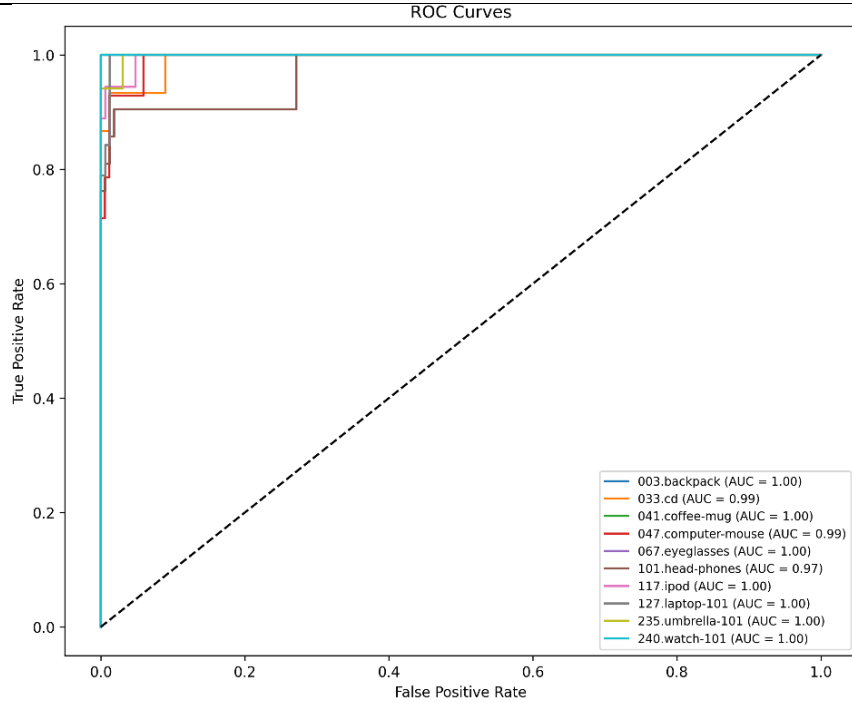


Figure 8. Confusion matrix for the final ResNet50 model under Gaussian blur (noise robustness test).

The minimal performance degradation under Gaussian blur, as shown in Figures 8 and 9, demonstrates strong robustness, a critical attribute for user-submitted photos that may suffer from motion, focus, or compression artifacts.

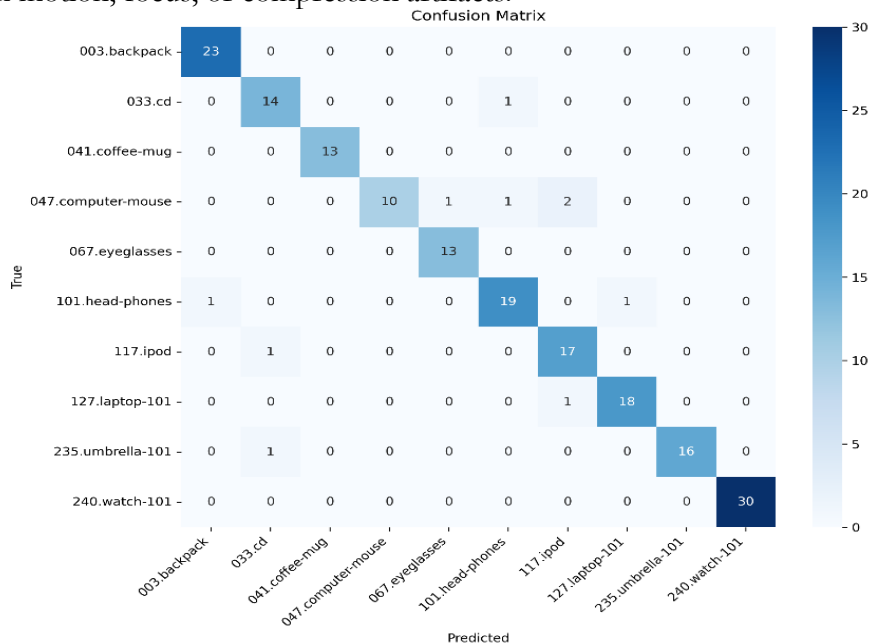


Figure 9. Confusion matrix for the final ResNet50 model on the Gaussian blur (noise) test set, illustrating robustness to simulated real-world image degradation.

Feature-Based Item Matching Performance:

The 2048-dimensional embeddings were derived from the final ResNet50 model to simulate the matching functionality. Cosine similarity was calculated between the simulated lost and found subsets. The model achieved a Top-1 matching accuracy of 89.01% (correct class match in the highest-similarity pair), and the Top-5 matching accuracy is 95.60% (correct class within the five highest similarities). The Average intra-class cosine similarity is 0.7286,

and the average inter-class is 0.6218. The distribution of cosine similarities between intra-class and inter-class pairs is shown in Figure 10.

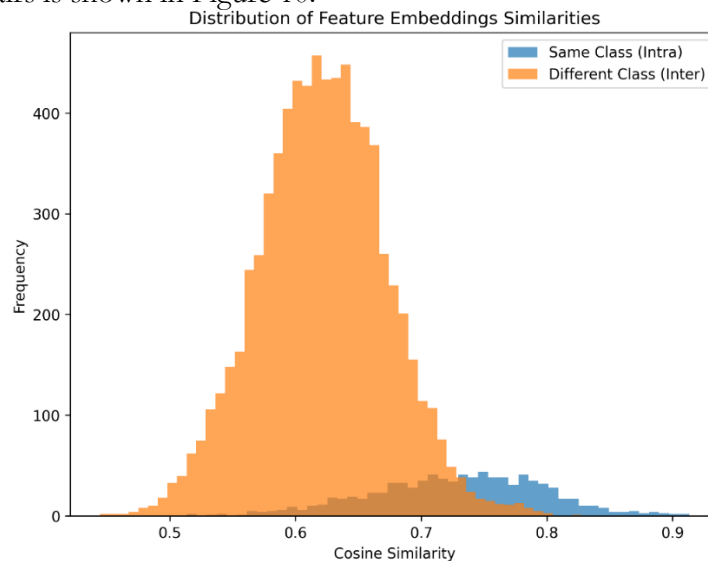


Figure 10. Distribution of cosine similarities between 2048-dimensional feature embeddings for intra-class and inter-class item pairs in the lost-and-found matching simulation.

The distinct separation between intra- and inter-class distributions confirms the discriminative power of the learned embeddings, facilitating reliable notification of potential matches while minimizing false positives.

Discussion of Results:

The experiment highlights the effectiveness of the suggested AI component. ResNet50 achieved the best performance; it has the best balance between high accuracy in classification, good performance in noise, and efficient inference. The top-5 matching accuracy exceeding 95% indicates strong potential for practical deployment.

The slight performance advantage of non-augmented training in cross-validation may reflect the relatively clean nature of the Caltech-256 images; however, augmentation proved beneficial in the noise test, underscoring its value for handling heterogeneous real-world inputs. Per-class analysis (via confusion matrices and ROC curves) revealed minor confusion among visually similar items (e.g., portable electronics), suggesting that multi-modal inputs (text description + image) could further enhance matching precision in future iterations.

These findings validate the AI engine as a reliable foundation for the integrated platform, where blockchain ensures tamper-proof logging of matches, IoT provides location context, and zero-knowledge proofs safeguard user privacy during verification. The achieved metrics compare favorably with prior works on object recognition for similar domains, positioning the system as a competitive solution for public-space item recovery.

Limitations:

While the proposed system shows impressive potential for the management of lost and found items in public places, it also has some limitations. The experimental evaluation of the AI was done on a filtered subset of the Caltech-256 dataset comprising 1,219 images across only 10 object categories, i.e., backpack, CD, coffee mug, computer mouse, eyeglasses, headphones, iPod, laptop, umbrella, and watch. Although these classes represent commonly lost portable items, the photos submitted by users often suffer from occlusions, varying lighting conditions, motion blur, partial views, complex backgrounds, and diverse angles. The robustness test using Gaussian blur showed only minor degradation (accuracy improved slightly to 94.54% from 93.99% on the clean test set), yet this single noise type does not fully capture the multifaceted degradations encountered in practice. Furthermore, the study

evaluated only the AI component in isolation. The integration of blockchain for immutable logging, IoT for real-time tracking, and zero-knowledge proofs (ZKPs) for privacy-preserving verifications remains conceptual and has not been empirically implemented or stress-tested for latency, throughput, or gas costs on a live blockchain network.

Future Scope:

The work done so far creates a solid base for a safe and smart lost and found platform. A critical next step is the utilization of large real-world datasets. In future studies, images should be collected and annotated directly from public places like universities and shopping complexes to capture authentic variations in lighting, occlusion, and user photography quality. Techniques like few-shot learning, domain adaptation, or synthetic data generation (using GANs or diffusion models) could bridge the gap between benchmark datasets like Caltech-256 and operational conditions. The integration of textual descriptions with visual features would improve matching precision, especially for items with similar appearances but distinct user-provided details (e.g., color, brand, or unique markings). Beyond lost-and-found items, the platform architecture has broader applicability in asset tracking (e.g., stolen vehicles, luggage in transit), pet recovery, and even humanitarian efforts (missing persons). In the future, this work can be extended by developing a complete end-to-end system and evaluating its practical usability.

Conclusion:

This research presents a blockchain and AI-based platform for efficient management of lost and found items in public places. The proposed system addresses critical shortcomings of traditional lost and found mechanisms by synergistically combining artificial intelligence for intelligent item classification and matching, blockchain for immutable and transparent record-keeping, Internet of Things (IoT) devices for real-time location tracking, and zero-knowledge proofs for privacy-preserving verifications. The experimental evaluation of the AI component was done on a subset of the Caltech-256 dataset (1,219 images across 10 relevant classes), demonstrating robust performance. ResNet50 emerged as the best architecture as it achieves 5-fold cross-validation accuracy of 94.79% (with augmentation) to 95.46% (without), holdout test accuracy of 93.99%, and strong noise robustness (94.54% under Gaussian blur). The feature-based matching module, which leverages 2048-dimensional embeddings and cosine similarity, attained Top-1 accuracy of 89.01% and Top-5 accuracy of 95.60%, with clear discriminative separation between intra- and inter-class similarities. These results are supported by extensive visualizations of learning curves, confusion matrices, per-class metrics, ROC curves, and similarity distributions, which validate the AI engine's readiness as the core matching mechanism. Collectively, the use of blockchain, AI, IoT, and ZKPs has the potential to significantly increase lost item recovery rates, reduce economic losses, alleviate user distress, and foster greater trust in public-space services. Future efforts toward real-world dataset curation, multi-modal intelligence, full-system deployment, and ethical safeguards will further realize the platform's transformative impact.

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The authors confirm that this manuscript has not been published previously and is not under consideration by any other journal. All authors have contributed significantly to the work, and all authors have read and approved the final version of the manuscript.

Author's Contribution:

Muhammad Mateen Sadiq collected the data and conducted the experiments. Sana Irshad supervised the work, coordinated all contributions, and finalized the manuscript for submission. Both authors reviewed and approved the final version of the manuscript.

Conflict of Interest:

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

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