HEROCS: An On-Device Mobile Computer Vision System for Hazard Detection in Household Environments

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Abstract

Household environments pose significant risks to young children aged 0–3 years, who spend over 70% of their waking hours indoors, interacting with objects that may cause choking, burns, poisoning, or falls. Existing computer vision (CV) systems for household safety often rely on binary safe/unsafe classifications and lack cultural context or nuanced risk assessment. To address these gaps, a Home Hazard Evaluation and Risk Object Classification System (HEROCS) is proposed which is a mobile-based CV system utilizing YOLOv8 for multi-label hazard detection, integrated with augmented reality (AR) for intuitive caregiver feedback. HEROCS employs a culturally relevant dataset of 5,373 images from Filipino households, annotated with hazard labels, and implements a risk scoring rubric aligned with UNICEF categories. Deployed on standard Android smartphones, HEROCS achieves real-time inference at 28–32 FPS on mid-range devices, computing a Household Danger Index (HDI) and delivering safety recommendations via interactive AR overlays. Testing in simulated Filipino household scenarios revealed 41.5% mAP@0.5, with strong performance on well-represented categories but lower recall on underrepresented classes. Usability testing yielded a System Usability Scale score of 44.5, indicating areas for improvement in user experience design.

Keywords: Computer Vision, YOLOv8, Child Safety, Household Hazards, Augmented Reality, Filipino Households

1 Introduction

Every day, a home transforms into an adventure playground for toddlers. As families rearrange décor, introduce new toys, and bring in cleaning supplies, the domestic landscape shifts constantly, often faster than parents or guardians can spot emerging dangers. Young children spend over 70 percent of their waking hours indoors interacting with furniture, appliances, and household items [1]. This extended exposure significantly increases the likelihood of injuries within the home, particularly for children aged 0–3, whose developmental milestones (crawling, early walking) increase their curiosity and mobility.

A study published in the journal *Injury* analyzed injury-related deaths across different age groups in India and found that both pediatric patients (under 15 years) and elderly individuals (over 64 years) experience significantly higher mortality when injuries occur at home compared to outside environments [2]. The researchers analyzed data from over 8,000 trauma patients and concluded that “in pediatric and elderly patients the chances of mortality was significantly higher when injured at home." These findings underscore the critical need to proactively identify and mitigate domestic hazards, especially in spaces frequented by young children aged 0–3 and elderly individuals.

Recent studies further affirm that children, especially those under five, are significantly more susceptible to home injuries compared to other age groups. Alamr et al. reported that 58.2% of children under five in Al-Baha, Saudi Arabia, experienced home accidents, with falls, burns, and poisoning being the most prevalent [3]. Similarly, during COVID-19 lockdowns, Er et al. observed a notable increase in pediatric emergency visits due to household incidents, particularly poisonings and foreign body ingestions [4]. Additionally, Cazacu-Stratu et al. found that many parents lacked sufficient knowledge and practices to prevent household injuries, emphasizing the need for enhanced caregiver education and proactive hazard management [5].

Children's natural curiosity and imitative behavior also contribute to their risk of encountering hazardous objects. Stengelin et al. found that children aged 4.6 to 6.5 years are more likely to over-imitate actions performed by adults and peers, suggesting that children learn object use through strong social modeling [6]. This behavior may inadvertently expose them to dangers if adult actions involve unsafe interactions with household items. Bosshart et al. further demonstrated that children misidentify hazardous household products, especially when those items have child-friendly characteristics such as colorful packaging or fruity scents, often confusing them with edible or safe objects [7]. Moreover, Orsagh-Yentis et al. reported a rise in children ingesting foreign objects such as coins and batteries during the COVID-19 pandemic, linking this trend to increased unsupervised time at home [8].

Ensuring the safety of children within household environments is paramount, as both indoor and outdoor settings present distinct and evolving risks. Active supervision combined with preventive strategies like safety gates, securing hazardous materials, and adult education have been shown to reduce these risks significantly [9]. Moreover, creating safe environments not only helps prevent injuries but also promotes healthy cognitive and motor development [10].

Home environments pose distinct challenges compared to industrial or public settings where CV-based risk assessments are already well established. In workplaces like construction sites or factories, hazards are often standardized (e.g., machinery, PPE compliance) and environments are structured, enabling predefined rules for detection [11,12]. In contrast, households are dynamic, cluttered, and personalized, with hazards ranging from unstable furniture to small choking objects that vary widely across cultures and living conditions [13,14]. For example, Filipino homes often include region-specific risks like unsecured bamboo furniture or localized cleaning supplies, which are rarely represented in generic datasets [15].

In response to these challenges, recent advancements in computer vision (CV) and artificial intelligence (AI) are opening new avenues for proactive safety interventions. CV has been widely applied in occupational health and safety particularly in construction and industrial settings for monitoring compliance, detecting hazards, and preventing accidents [11, 12]. However, its use in indoor environments like homes is still emerging. Studies are now exploring how CV can assist with detecting fire risks, identifying obstacles, and assessing accessibility [16, 17].

Despite these advancements, existing AI and CV systems for household child safety remain limited in addressing the dynamic, context-dependent risks of home environments. Most systems use binary safe/unsafe classifications without quantifying risk severity or accounting for contextual factors such as object location, accessibility, or child behavior [13, 14]. These limitations underscore the need for more nuanced, context-aware approaches to household hazard detection, particularly those adapted to culturally specific environments.

Building on the limitations identified in current systems and the urgent need for context-aware solutions in household safety, this study proposes HEROCS (Home Hazard Evaluation and Risk Object Classification System), a mobile-based computer vision application incorporating augmented reality (AR) and real-time scanning tools designed to address these gaps. HEROCS is specifically designed to identify, evaluate, and prioritize household hazards in real time, particularly those that pose risks to young children aged 0–3, by adopting a multi-label framework, enabling it to assign multiple risk attributes to a single object.

2 Related Work

2.1 Computer Vision for Household Safety

Studies are now exploring how CV can assist with detecting fire risks, identifying obstacles, and assessing accessibility in indoor environments [18, 19]. Despite these advancements, existing AI and CV systems for household child safety remain limited in addressing the dynamic, context-dependent risks of home environments. Few studies focus on accurately identifying and evaluating hazards using these technologies, and those that do lack a robust framework for assigning hazard levels to detected objects [13, 14].

Most systems classify objects as broadly "safe" or "unsafe" without quantifying risk severity or contextual factors. They also lack context-awareness, failing to account for how the location, accessibility, or child behavior influences hazard severity. Furthermore, existing datasets rarely reflect the cultural and environmental characteristics of typical Filipino households, limiting their real-world applicability.

2.2 Augmented Reality for Safety Applications

Su et al. introduced RASSAR, a mobile augmented reality system for scanning indoor environments to detect accessibility and safety hazards [18]. The system adopts a structured rubric-based approach aligned with professionally recognized accessibility standards, including the Americans with Disabilities Act (ADA) and the Home Safety Self-Assessment Tool (HSSAT). This categorization approach reflects a deeper integration of structured safety criteria than most CV systems in the household domain. AR has been shown to improve hazard recognition in construction safety education [20], demonstrating its potential for household safety applications.

2.3 Multi-Label Classification for Hazard Detection

Khan and Dey developed a deep learning model using their ChildSUn dataset to classify objects as either child-safe or unsafe, achieving 99.63% accuracy using EfficientNet-B0 [13]. However, their model classifies objects in binary terms without assessing varying levels or types of risk. Argoncillo et al.'s indoor object detection framework demonstrated that object detection can effectively monitor safety-critical elements in home environments when combined with context-aware algorithms [14]. Multi-label classification methods have been comprehensively studied [21], providing foundational techniques for HEROCS' implementation.

Gao et al. proposed a multimodal fusion approach for elderly hazard detection, combining RGB and depth data [19]. While promising, their work does not integrate standardized safety guidelines or domain expert validation, and their custom dataset includes a limited range of hazard types.

3 Methodology

3.1 Conceptual Framework

HEROCS is grounded in Bronfenbrenner's Ecological Systems Theory [31], focusing on the home microsystem where children interact with hazardous objects. The system evaluates contextual factors (e.g., object reachability, spatial relationships) to assess risk, aligning with developmental safety needs. By incorporating object height, location, and accessibility into risk assessment algorithms, HEROCS operationalizes Bronfenbrenner's emphasis on environmental influence.

The system development followed Agile Scrum methodology [32], dividing work into eight iterative sprints covering dataset preparation, model training, multi-label classification, AR integration, risk scoring, spatial awareness, testing, and deployment.

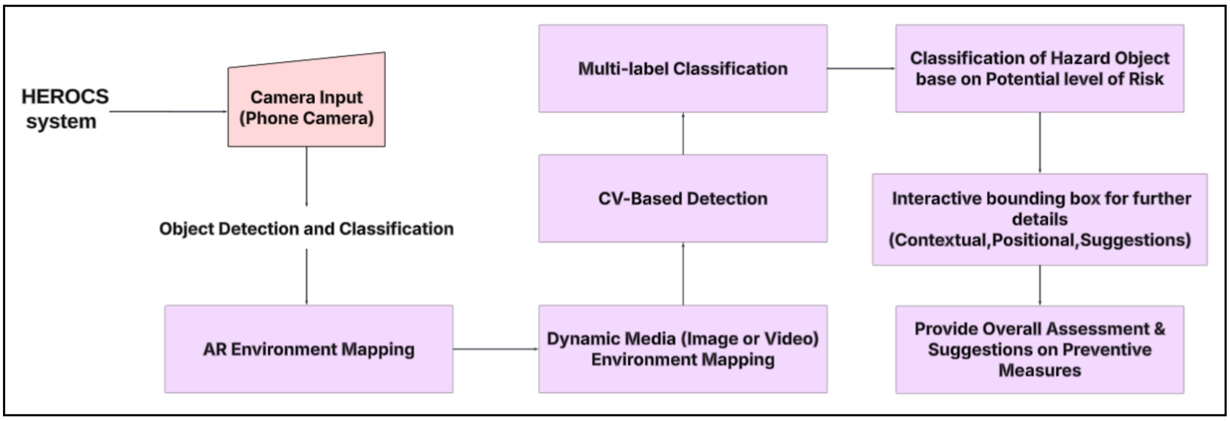

Figure 1: HEROCS system architecture.

Figure 1 illustrates the HEROCS system architecture, which processes camera input through a sequential pipeline: (1) Object Detection and Classification identifies potential hazards using YOLOv8, (2) AR Environment Mapping overlays visual indicators in real-time, (3) Dynamic Media Mapping processes image or video streams, (4) CV-Based Detection performs real-time object recognition, (5) Multi-label Classification assigns multiple risk attributes per object, (6) Classification of Hazard Objects determines risk levels (0.1-0.4 scale), (7) Interactive Bounding Boxes provide contextual safety suggestions, and (8) Overall Assessment generates the Household Danger Index with preventive measures.

3.2 Research Approach

HEROCS adopts a constructive research approach, rooted in design science research (DSR) methodologies, which emphasizes the creation and evaluation of innovative artifacts to solve practical, real-world problems while simultaneously contributing to theoretical understanding [22]. The constructive approach is particularly suitable for technological innovation in human-computer interaction (HCI) and safety-critical domains, where novel solutions must be both functional and context-aware [23].

The approach supports iterative design and development processes [24], integration of domain expertise with technical innovation [25], and empirical validation through multiple evaluation methods [26]. Recent studies in similar domains have successfully employed constructive methodologies [27], demonstrating their effectiveness for creating practical yet theoretically grounded solutions in smart home applications [28]. Considerations of AI safety [29] and algorithm aversion [30] informed the system's design to ensure user acceptance.

3.3 Dataset Construction

A comprehensive dataset of 5,373 images was created through a two-phase constrained augmentation strategy, addressing severe class imbalance identified in the initial 1,500-image collection. The dataset captures culturally relevant Filipino household objects including bamboo furniture, local cleaning agents, and region-specific hazards. Images are annotated with multi-label tags (e.g., "sharp," "within reach," "choking hazard") and categorized into four risk levels (Low, Moderate, High, Highly Dangerous) based on UNICEF standards and expert consultations [33]. HEROCS dataset details are available via github at https://github.com/riggsybanez/HEROCS-Project.

The augmentation strategy was informed by established techniques in deep learning [34,35] and employed priority-based image selection for minority classes using SMOTE principles [36], hard augmentation cap of three per image to prevent overfitting [37], dynamic early stopping to maintain dataset quality [38], and selective downsampling of majority classes (surface_edge: 1,673 to 851 instances) to address imbalanced data [39].

This approach improved the class balance ratio by 7.9× (from 836:1 to 106:1) and reduced standard deviation by 36%, while avoiding over-augmentation artifacts. The dataset addresses gaps in Philippine-specific child injury data [40,41] and includes hazards documented in local safety reports [42].

3.4 Model Training

HEROCS leverages YOLOv8s (11.2M parameters), fine-tuned on Google Colab Pro with NVIDIA Tesla T4 GPUs, for real-time object detection. The model is optimized for low-light conditions common in Filipino homes [43] using image augmentation and contextual labeling. YOLOv8 was selected based on its superior performance for small object detection [44, 45] and real-time processing capabilities [46].

Training configuration includes:

- Training schedule: 120 epochs with early stopping patience=30
- AdamW optimizer: lr=0.001, lrf=0.0001, momentum=0.937
- Regularization: weight decay=0.0005, dropout=0.3
- Class weighting: classification loss weight=0.5 (mitigating residual imbalance)
- Loss formulation: CIoU for bounding box regression, binary cross-entropy for classification [47]

- Batch size: 20, image size: 640×640
- Mixed precision (AMP) enabled for efficiency [48]

Performance is evaluated via precision, recall, F1-score, and mean Average Precision (mAP) following standard object detection metrics [49]. The model was fine-tuned using transfer learning principles [50] to preserve general detection capabilities while adapting to Filipino household hazards.

3.5 Hazard Scoring Rubric

A scoring rubric (0.1–0.4) assigns risk levels based on severity, accessibility, and contextual factors (e.g., object height, location). The framework evaluates objects across three dimensions:

Categorical attributes: Inherent danger properties (sharp, toxic, flammable, electrical) based on documented hazard types [51–53]

Positional attributes: Child accessibility based on WHO growth standards [54]—floor-level (0-30cm), within-reach (30-96cm), elevated (>96cm)

Contextual attributes: Edge proximity, security states, spatial relationships informed by home safety frameworks [53, 55]

Each detected hazard receives a risk score synthesizing these dimensions, with individual scores aggregated to compute the Household Danger Index (HDI) ranging from 0.1 (safe) to 0.5 (critically unsafe). The HDI model builds on the validated Home and Environment Risk Rating Scale (HERRS) [55], applying similar severity weights through automated computer vision analysis.

3.6 Augmented Reality Integration

ARCore and Flutter enable real-time AR overlays, projecting interactive bounding boxes with hazard labels and safety recommendations onto the smartphone camera view. The AR interface employs augmented reality principles [56] with evidence-based design for hazard recognition [20] which include 1) color-coded bounding boxes: red (high-risk), orange (moderate-risk), yellow (low-risk), 2) interactive tap-based information display showing object name, hazard labels, risk level, and safety recommendations, 3) frame throttling for performance optimization, and 4) stable 28-32 FPS rendering with 220-280ms end-to-end latency.

3.7 Multi-Label Classification

The system applies a multi-label classification approach [21] to identify multiple co-occurring hazard characteristics within a single object. Unlike traditional single-label classification models, the multi-label framework allows assignment of label combinations (e.g., “sharp,” “within reach,” “unsecured”) that better reflect real-world complexity.

Classification logic is implemented through the RiskClassification class, which maps 24 object classes to intrinsic hazard properties. Label assignment is guided by expert-defined taxonomies and safety standards, ensuring outputs align with recognized child safety protocols [33].

4 Results and Discussion

4.1 Detection Performance

The YOLOv8s model achieved a mean Average Precision (mAP@0.5) of 41.5%, with precision of 54.5% and recall of 41.9%. This represents an 8.9% improvement over the initial YOLOv8n baseline (38.1% mAP@0.5), with a particularly notable 21.4% relative gain in recall. Performance varied significantly by category, as shown in Table 1.

Table 1: YOLOv8s Performance Metrics by Hazard Category

Category	**Precision**	**Recall**	**mAP@0.5**
Toxic Chemical	0.687	0.583	**0.615**
Lead Paint	0.580	0.583	0.602
Hot Container	0.852	0.608	0.746
Small Toys/Beads	0.506	0.545	0.351
Electrical Outlets	0.295	0.160	0.148
Cleaning Products	1.000	0.000	**0.006**
Fragile Objects	0.511	0.112	0.118

The model exhibits overfitting with a validation-to-training loss ratio of 3.24, suggesting the 11.2M parameter architecture exceeds optimal capacity for the 5,373-image dataset. This indicates the need for additional regularization strategies or dataset expansion to 8,000-10,000 images.

4.2 Functionality and Accuracy Testing

System-level testing in simulated Filipino household environments achieved a 60% pass rate (3 of 5 test cases) for functionality, with successful detection and correct risk label assignment when objects appeared in camera view. However, detection failures occurred in 40% of scenarios, primarily attributed to dataset imbalance and environmental factors such as occlusion or suboptimal positioning. Low-light conditions common in Filipino households with limited electrical infrastructure further impacted detection, particularly for chemical hazards requiring package detail recognition.

Contextual accuracy testing showed 60% perfect score matching between expected and actual risk assessments, validating the multi-dimensional classification algorithm's ability to synthesize categorical, positional, and contextual labels. However, systematic underestimation patterns emerged in 40% of cases, indicating that hazard weighting coefficients for chemical substances require recalibration.

4.3 System Performance

Through optimization strategies including frame throttling (processing every 3rd frame) and limiting concurrent hazard tracking to 15 objects, the system achieved stable rendering performance of 28–32 FPS with 220–280ms end-to-end latency on mid-range Android devices. This ensures the AR interface remains responsive during active scanning across diverse hardware configurations (4GB to 8GB RAM, Android 13-15). Preprocessing employed direct resizing of camera frames to 640×640, which may introduce geometric distortions across devices with varying aspect ratios (16:9 to 20:9).

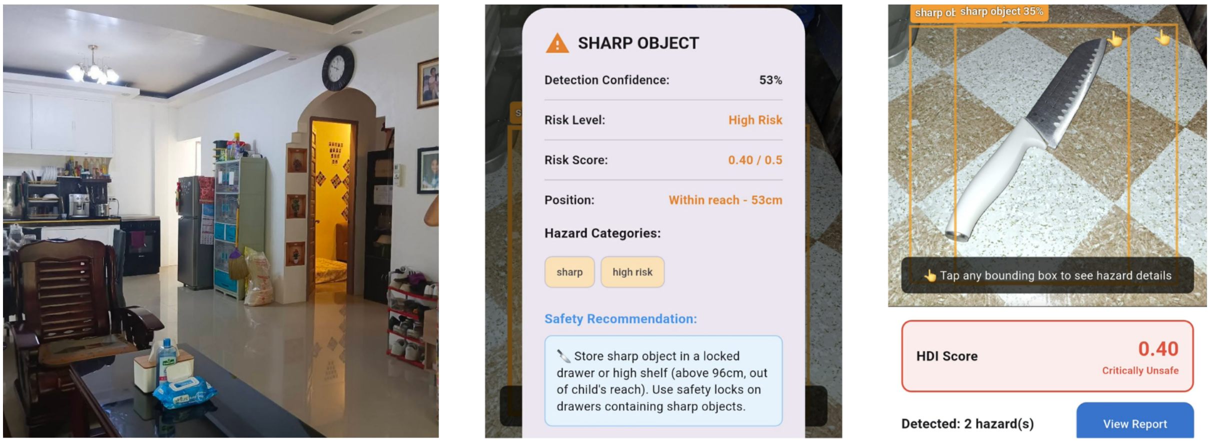

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Figure 2: Sample outputs: (a) sample image from the dataset (b) preventive suggestion interface, and (c) detected hazardous object with a bounding box and risk score.

4.4 Usability and Reliability Testing

Usability testing with 5 participants yielded a System Usability Scale (SUS) score of 44.5, falling below the deployment readiness benchmark of 68 [57]. While participants found core functions generally well-integrated and did not require extensive technical support, the results indicated significant barriers to ease of use. Reliability testing demonstrated excellent internal consistency with Cronbach's alpha of 0.876 [58], confirming that SUS questionnaire items reliably measured perceived usability.

Key usability challenges identified include: difficulty tracking hazards in cluttered environments, uncertainty about color-coded severity levels without explicit legend, mixed confidence regarding frequent use, and bounding box overlap in dense environments.

4.5 Limitations

Several critical limitations constrain full deployment readiness:

Dataset imbalance: Despite augmentation efforts, minority classes (furniture_unstable: 8 instances, exposed_metal_bed_frame: 12 instances) remain critically underrepresented. Multi-label co-occurrence challenges prevented isolated augmentation when rare objects appeared alongside majority classes.

Expert validation: The risk level assessment and hazard classification framework would benefit from formal validation through Cohen's Kappa inter-rater reliability testing with certified child safety professionals. While consultations with concerned agencies provided valuable insights, systematic psychometric validation against independent professional evaluations represents an important direction for future research to strengthen the empirical foundation of the scoring framework.

Spatial reasoning: The system lacks true 3D scene understanding or room boundary recognition, causing HDI score inflation when scanning across doorways. Fixed 150cm camera height assumptions degrade positional accuracy when users scan from non-standard heights. Temporal lighting variations between morning and afternoon scanning sessions were not systematically evaluated.

Limited user testing: Comprehensive end-user validation with diverse caregiver populations across different socioeconomic backgrounds is limited and requires further testing. The perceived usefulness, clarity, and actionability of safety recommendations from non-technical user perspectives require further empirical verification.

5 Conclusion

HEROCS establishes a proof-of-concept for an on-device, culturally aware hazard detection system tailored to Filipino households. By expanding the dataset to 5,373 images through constrained augmentation and employing multi-label classification, the system addresses specific risks found in Filipino homes. The YOLOv8s model achieved 41.5% mAP@0.5 and 41.9% recall, demonstrating functional capabilities for well-represented categories while highlighting critical dataset limitations for minority classes.

The system successfully integrates AR visualization with color-coded risk indicators and interactive safety recommendations, achieving real-time performance (28-32 FPS rendering, 220-280ms latency) on mid-range Android devices. However, the SUS score of 44.5 indicates significant usability barriers requiring interface refinement. The Household Danger Index provides environment-level risk quantification, though spatial reasoning limitations affect accuracy.

Most critically, the absence of formal expert validation through Cohen's Kappa reliability studies means the hazard taxonomy and risk scoring framework represent literature-grounded research determinations rather than empirically validated expert consensus. This limits deployment readiness for safety-critical child protection applications requiring $k \geq 0.75$ agreement benchmarks.

Future work must prioritize: (1) dataset expansion to 8,000-10,000 images with minimum 200-300 instances per class through targeted photography and synthetic generation; (2) formal partnerships for Cohen's Kappa validation studies with certified professionals; (3) integration of depth sensors for accurate 3D spatial reasoning; (4) comprehensive usability validation with 10-15 diverse caregivers; (5) longitudinal randomized controlled trials measuring pediatric injury incidence rates; (6) aspect-aware preprocessing strategies to address geometric distortions from direct resizing of varying smartphone aspect ratios (16:9 to 20:9) to YOLO's 640×640 input.

Despite these constraints, HEROCS demonstrates that on-device mobile computer vision can be adapted for culturally contextualized household hazard detection. The study contributes methodological frameworks for hazard dataset creation in underrepresented populations and establishes technical architecture for multi-dimensional classification on mobile devices.

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