VISION-BASED DETECTION OF BROKEN GLASS HAZARDS ON COMPLEX FLOOR TEXTURES

Research proposal

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1 Declaration

I, **D M Tharindu Lakshimal Disanayaka** (2020/ICT/107), do hereby declare that the work reported in this research proposal was carried out independently by me under the supervision of **Dr. T. Kartheeswaran, Senior Lecturer, Department of Physical Science, Faculty of Applied Science, University of Vavuniya**. This proposal describes the results of my own research, except where due reference has been made in the text. No part of this research project has been submitted earlier or concurrently for the same or any other degree.

Date: _______________ Signature: _________________________

Certified by:

1. Supervisor: Dr. T. Kartheeswaran Date: ________________
Signature: __________________________

Approved by Coordinator/ IT4216
Name: Date: ________________
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Approved by Head/ Department of Physical Science
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2 Introduction

2.1 Background

The autonomous service robot industry has evolved rapidly over the last two decades, transitioning from simple collision-based navigation to sophisticated spatial mapping. Modern households increasingly rely on these devices for "set-and-forget" cleaning, trusting in their ability to navigate complex environments autonomously. However, despite the integration of advanced navigation systems, the fundamental technology powering these devices faces a critical safety limitation: the inability to detect transparent hazards such as broken glass fragments.

This failure is not merely a software oversight but stems from the physical limitations of current sensor hardware. Most modern robots rely on Light Detection and Ranging (LiDAR) or RGB-Depth (RGB-D) cameras to map their surroundings. As noted by Linus & Rueckert (2023), transparent objects are effectively invisible to these sensors because laser beams pass directly through the material or refract unpredictably [1]. Instead of registering an obstacle, the sensor receives no return signal (or an erroneous one), causing the robot's mapping algorithm to interpret the dangerous area as empty, navigable space [2]. Similarly, RGB-D cameras struggle because transparent glass lacks the "prominent texture features" required for accurate depth estimation algorithms [3].

Compounding this hardware blindness is a significant gap in artificial intelligence training. Even if a robot's optical camera captures a visual image of the floor, the navigation system lacks the "semantic knowledge" to recognize the danger. Huang (2023) identifies that current robotic datasets are largely restricted to the classification of common, opaque objects like shoes, cables, or furniture [4]. There is a distinct absence of labeled training data for small, irregular, and transparent debris. Consequently, without a trained model to flag these irregularities, the robot's vision system treats glass shards as part of the cleanable floor surface rather than a hazard to be avoided [5], potentially damaging the appliance and spreading hazardous debris.

2.2 Problem Definition

Current robotic navigation systems suffer from a dual failure: physical sensors (LiDAR) look through glass, and current algorithms lack the training data to recognize irregular shards [4]. There is currently no standardized computer vision framework capable of detecting **broken glass fragments** (clear and colored) on complex floor textures.

2.3 Research Objectives

- To construct a novel dataset, **"Glass-Floor-2026"**, containing annotated images of broken clear and colored glass (medical/beverage bottles) on Tile and Cement floors.

- To train and optimize a vision model (YOLO) to identify irregular shard boundaries based on refractive distortions.
- To evaluate the model's performance across different lighting conditions (Daylight vs. Artificial Light) and glass colors.

2.4 Motivation

The primary motivation for this research stems from the unique intersection of modern domestic robotics and the specific living conditions found in Sri Lankan households. While the adoption of autonomous cleaning robots is growing locally, the technology's current inability to detect glass poses a disproportionate risk in this context due to distinct cultural and architectural norms.

In Sri Lanka, the indoor environment is predominantly characterized by hard flooring surfaces such as ceramic tile, polished cement, or terrazzo. Based on housing data from the Department of Census and Statistics [6], it is estimated that approximately 90% of local homes utilize these hard surfaces (Table 1) rather than the carpeting often found in Western markets. This architectural reality creates a specific mechanical hazard known as the "Pressure-Drag" effect. When a robot blindly traverses broken glass on a hard surface, the shards are not cushioned; instead, they are pressed into the robot's rubber wheels and dragged across the floor. This interaction effectively turns the robot into an abrasive tool, simultaneously destroying the expensive floor finish and causing catastrophic damage to the robot's internal vacuum motors.

Table 1: Prevalence of Floor Types (Source: [6]) and Author's Risk Assessment based on Fracture Mechanics.

Floor Type	**Est. Prevalence**	**Hazard Interaction Risk**
Ceramic/Porcelain Tile	65%	**Critical:** High shatter radius; injury risk.
Cement/Terrazzo	25%	**High:** Shards blend into gray texture.
Wood/Parquet	5%	**Medium:** Shards embed into grain.
Carpet/Rug	5%	**Low:** Shards remain localized.

Beyond the financial implication of damaged appliances and flooring, the motivation is deeply rooted in public health and safety. Walking barefoot indoors is a pervasive cultural norm in Sri Lanka. Consequently, the "blind spots" of a robot vacuum are not just inconveniences but physical dangers. When a medical bottle or glass tumbler shatters, the fragments scatter widely on hard tiles. Since current robots cannot detect and avoid these areas, they fail to clean the hazardous debris effectively, leaving dangerous sharp edges capable of causing severe laceration injuries. This risk is particularly acute for vulnerable household members, such as toddlers and pets, who spend significant time on the floor. Successful detection is therefore the critical first step; once a robot can "see" the glass, future systems can be developed to alert users, preventing these injuries entirely.

In summary, this project is motivated by the urgent need to address the safety gap where current autonomous navigation technologies fail to detect transparent hazards. Despite the sophistication of modern LiDAR and camera systems, they lack the specific training data required to identify broken glass, leaving a dangerous void in home safety automation. By developing a specialized detection model, this research aims to bridge the gap between "smart" navigation and actual domestic safety, ensuring that robotic assistants do not become hazards in the very homes they are meant to clean.

3 Related Works

Table 2: **Summary of Related Works and Identified Research Gap.** Existing methods focus on large household objects or opaque debris, ignoring hazardous transparent fragments.

Author (Year)	**Target Object**	**Methodology**	**Limitation (Gap)**
Xie et al. (2021) [7]	Glass Cups & Windows	Trans2Seg (Transformer)	Focuses on standing whole objects; ignores broken shards.
Sajjan et al. (2020) [8]	Transparent Objects	ClearGrasp (3D Shape)	Requires high-compute depth estimation; too heavy for mobile robots.
Zhou et al. (2017) [5]	Thin Obstacles	Vision-Based	Explicitly states inability to handle transparent/textureless objects.
Huang (2023) [4]	Floor Debris (Socks/Wires)	Lightweight CNN	Restricted to opaque objects; no training data for glass.
Proposed Work	**Broken Shards (Clear & Colored)**	**YOLO Based Segmentation**	**Optimized for floor-level debris and refractive edges.**

4 Research Gap

4.1 Current State of Transparent Object Detection (TOD)

Recent literature (2021-2025) highlights significant strides in computer vision. Xie et al. (2021) introduced the Trans10K dataset [7], utilizing vision architectures to segment large glass objects like doors and partitions. Similarly, Zhang et al. (2022) proposed Trans4Trans [9], optimizing these models for inference speed.

However, a critical limitation remains: these TOD studies focus exclusively on **intact, vertical structures** (e.g., windows, shelves). While commercial robotics has successfully addressed *opaque* floor hazards such as pet waste and cables current research completely overlooks **transparent floor level debris**. This leaves a specific blind spot: algorithms that can detect "glass" cannot look down, and algorithms that look down cannot see "glass."

4.2 The Gap in Debris Detection

As emphasized by Huang (2023), current robots are restricted to simple binary classification and lack the ability to identify specific types of small debris [4]. This creates a significant gap for "unstructured" hazards like broken medical bottles, which present both transparency and color challenges.

4.3 Quantifying the Sensor Gap

Current literature demonstrates high proficiency in detecting standard, opaque waste. As shown in Figure 1, state-of-the-art models like Mask R-CNN and ResNet achieve classification accuracies exceeding 96% for common debris [4]. However, this high performance is strictly limited to visible objects. The complete absence of performance data for **transparent glass detection** in these studies highlights the critical "blind spot" that this research aims to address.

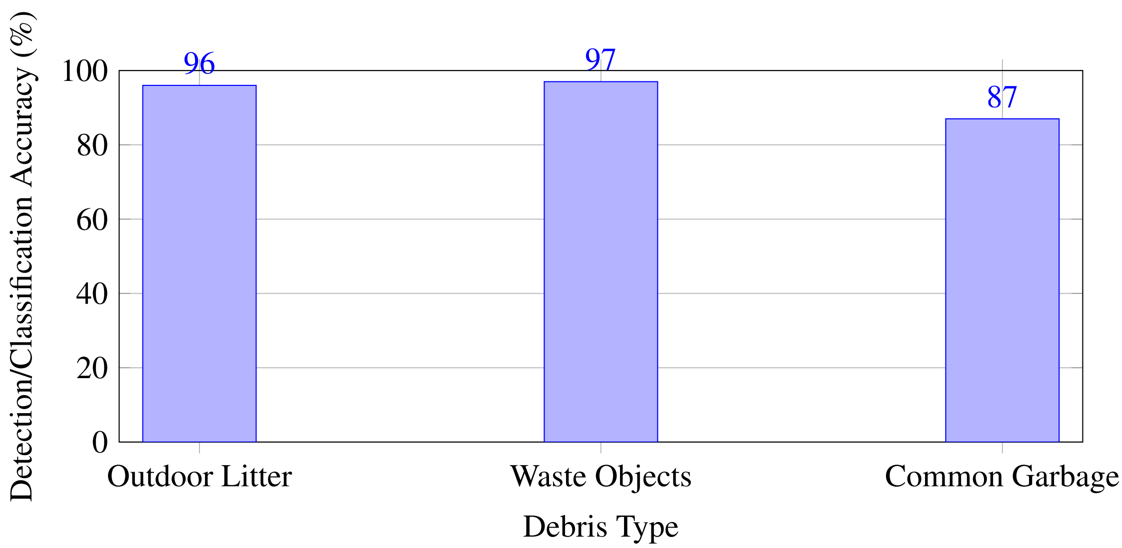

Figure 1: **The Research Gap.** While existing models achieve high accuracy (>87%) for opaque waste [4],[2].

5 Materials and Methods

The research follows a quantitative experimental approach designed to address the detection gap identified in the previous section. The complete system workflow, from the robot's visual input to the final evaluation, is illustrated in Figure 2.

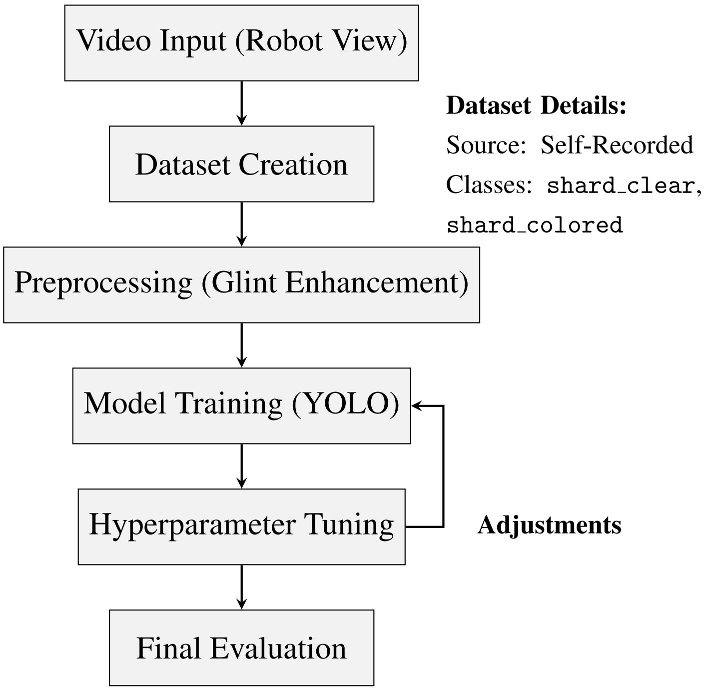

Figure 2: **Proposed System Workflow.**

5.1 Dataset Explanation

Since no public dataset exists for broken glass fragments in domestic environments, a custom dataset will be generated to ensure the system is robust against real-world household conditions.

- **Source:** Primary data collected using a 1080p camera mounted at a 15cm height to simulate the specific perspective of a cleaning robot.
- **Composition:** The dataset comprises 1,500 images covering two specific classes: broken Clear Glass and Colored Glass (Amber/Green).
- **Data Type:** Real-world images rather than synthetic data, ensuring diversity in lighting conditions (e.g., natural sunlight and ceiling lights) and floor patterns (e.g., polished cement, multi-colored ceramic tiles, and complex textures)

5.2 Algorithm Selection

The system utilizes the **YOLO** segmentation architecture. The specific model version (e.g., v8, v10, or v11) will be selected based on the highest performance accuracy and inference speed achieved on the custom dataset.

This vision model was selected over standard object detectors for specific reasons:

- **Irregular Shapes:** Broken glass shards do not have uniform geometric shapes.
- **Pixel-Level Precision:** Unlike bounding boxes, which include the background floor area, segmentation traces the exact pixel boundary of the shard. This provides precise localization data for the robot's path-planning algorithm to avoid tire damage.

5.3 Potential Challenges

Implementing vision-based detection for transparent objects presents specific technical hurdles that this research aims to address:

- **Lighting Sensitivity:** The model relies heavily on specular reflections (glints) to define shard boundaries. As noted by Wang & Li (2024), textureless transparent objects are difficult to segment without specific lighting conditions [3].
- **Texture Confusion:** Highly patterned flooring (e.g., terrazzo or complex ceramic designs) may create "visual noise," potentially leading the model to misclassify floor patterns as colored glass fragments.
- **Hardware Constraints:** Training the YOLO model on high-resolution video frames requires significant GPU computational resources, which may limit the batch size and training speed during the optimization phase.

6 Expected Outcome

1. **Validated Dataset:** A comprehensive dataset ("Glass-Floor-2026") containing over 1,500 annotated instances of clear and colored glass shards.
2. **Detection Model:** A trained vision model optimized for the identification of transparent hazards. The research will establish a performance benchmark by:
    - Analyzing the detection accuracy of *Colored Glass* (high-visibility instances).
    - Evaluating the sensitivity of the model toward *Clear Glass* (low-visibility/transparent instances).
3. **Performance Analysis:** A comparative study assessing detection success rates across different surface textures.

4. **Framework for Vision Enhancement:** A validated methodology demonstrating that standard robot cameras can be effectively trained to detect transparency. This provides a foundational baseline and a proof-of-concept for integrating safety-critical hazard detection into future commercial robotic vacuums.

7 Ethical Approval

No ethical approval is required. The study uses only inanimate objects (glass shards) and floor textures. No human subjects, animals, or sensitive private data are involved.

8 Gantt Chart

Work/Time (Months)	**Nov-25**	**Dec-25**	**Jan-26**	**Feb-26**	**Mar-26**	**Apr-26**	**May-26**	**Jun-26**
Title selection								
Proposal								
Literature Review								
Resource gathering								
Tools and Techniques								
Implementation								
Writing								
Publication / Conferences								
Presentation and Submission								

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