Multi-Modal Icon Vision System

Capstone Project Report

MID SEMESTER EVALUATION

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August 2025

ABSTRACT

The Multi-Modal IconVision project presents an advanced icon detection system for smartphone screenshots utilizing computer vision and deep learning techniques. By leveraging the YOLOv8 Nano architecture, we develop a lightweight yet powerful model capable of accurately identifying and classifying UI icons. The system is designed around a two-stage detection pipeline: first identifying potential UI element regions using YOLOv8's anchor-free detection mechanism, with the goal of later applying semantic analysis for functional classification. Our approach addresses critical challenges in mobile UI understanding including small object detection and semantic context integration, which will be addressed through a planned late fusion of OCR and visual data. The model achieves enhanced accuracy through the integration of a CSPDarknet53 backbone and C2f modules. The system will be complemented by an interactive web application enabling real-time screenshot upload and visualization of detected icons. This research contributes to accessibility enhancement, automated UI testing, and user experience analysis.

DECLARATION

We hereby declare that the design principles and working prototype model of the project entitled **Multi-Modal Icon Vision System** is an authentic record of our own work carried out in the Computer Science and Engineering Department, TIET, Patiala, under the guidance of **Dr. Jyoti** and **Dr. Surjit Singh** during 6th semester (2025).

Date: August 22, 2025

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
CNN	Convolutional Neural Network
GUI	Graphical User Interface
HCI	Human-Computer Interaction
mAP	Mean Average Precision
OCR	Optical Character Recognition
QA	Quality Assurance
SRS	Software Requirement Specification
UI	User Interface
UML	Unified Modeling Language
UX	User Experience
YOLO	You Only Look Once

INTRODUCTION

1 Project Overview

The proliferation of smartphones has fundamentally altered Human-Computer Interaction (HCI), with the graphical user interface (GUI) serving as the primary medium. Within these GUIs, icons have emerged as a universal, language-agnostic tool for navigation and functionality, condensing complex actions into simple, recognizable symbols. However, this symbolic abstraction, while beneficial for human users, presents a significant challenge for automated systems. The field of computational user interface understanding aims to bridge this gap by enabling machines to perceive, interpret, and interact with UIs in a human-like manner. This project fits into the broader trend of applying AI to enhance the software development lifecycle, from design and testing to accessibility compliance.

The Multi-Modal Icon Vision System is a dedicated effort within this field, focusing on the critical task of icon detection and semantic interpretation from static smartphone screenshots. This report details the development of a sophisticated system that leverages state-of-the-art computer vision and deep learning to achieve this goal. Our approach centers on the integration of the YOLOv8 architecture, a highly efficient real-time object detector, with advanced multi-modal learning techniques. This fusion creates a lightweight yet powerful framework capable of not only locating icons but also understanding their purpose.

The system employs a two-stage pipeline. The first stage, powered by YOLOv8's anchor-free detection mechanism, rapidly identifies potential UI element regions within a screenshot. The second stage is designed to apply a deeper semantic analysis, which will combine visual features from the detector with contextual cues (such as nearby text extracted via Optical Character Recognition) to perform a functional classification. The current phase focuses on establishing a robust visual detection foundation. A key component of our solution is the interactive web application that serves as a proof-of-concept, demonstrating the practical utility of our approach.

2 Need Analysis

The development of an accurate and efficient icon detection system for mobile screenshots addresses several critical technological and societal needs. **Accessibility Enhancement:** Digital accessibility is a paramount concern. For instance, a banking app might use a small, unlabelled '+' icon to add a beneficiary. For a sighted user, this is intuitive, but for a user with a screen reader, it is an impassable barrier. Our system aims to provide the semantic text label "Add Beneficiary" for such cases, making applications more inclusive. **Automated UI Testing and Quality Assurance:** The mobile ecosystem is heavily fragmented. Consider a social media app updating its 'like' icon from a heart to a thumbs-up. Automated visual regression testing using our system can programmatically flag this change, ensuring design consistency or intended rebranding is verified across dozens of device screens simultaneously, a task that is infeasible for manual QA teams. **User Experience (UX) Research and Analytics:** Understanding user interaction requires detailed analysis. Our system enables researchers to automatically tag and analyze icon utilization across large datasets of user sessions, providing granular insights into which features are popular, where users struggle, and how the interface design can be optimized.

3 Research Gaps

Our comprehensive literature review identified several significant gaps that this project aims to address:

1. **Small Object Detection in Mobile Interfaces:** Mainstream object detection models often perform poorly on UI icons smaller than 32x32 pixels, as pooling layers in CNNs can lose the required fine-grained spatial information. The consequence is that automated tools frequently miss critical interactive elements, leading to incomplete analyses.

2. **Semantic Understanding Integration:** Most existing tools focus on purely visual detection. They lack the ability to integrate semantic context to understand an icon's function. This leads to ambiguity, where visually identical icons used for different purposes (e.g., a plus symbol for "add item" versus "zoom in") cannot be distinguished.

3. **Real-time Performance:** Many accurate detection models are too computationally expensive for on-device applications or interactive web tools. This limits their practical application to offline batch processing, preventing their use in real-time assistive technologies or interactive development tools.

4. **Comprehensive and Specialized Mobile UI Datasets:** There is a shortage of large, meticulously annotated datasets specifically for mobile icon detection and functional classification. The lack of high-quality training data is a major bottleneck for research in this area.

5. **Integration of Multiple Detection Modalities:** Most current approaches are unimodal, relying solely on visual information. The optimal strategies for fusing visual features with text from OCR in the UI domain are still an open research area.

4 Problem Definition and Scope

Problem Statement: Mobile applications increasingly rely on icons to convey functionality. However, automatically detecting, classifying, and understanding these icons presents significant technical challenges due to their diverse visual characteristics, varying sizes, contextual dependencies, and semantic complexity. **Scope of Work:** Our project encompasses the development of a complete icon detection pipeline including:

- Creation and annotation of a comprehensive mobile icon dataset
- Development of an enhanced YOLOv8-based detection model
- Design of a multi-modal learning architecture for semantic understanding
- Implementation of real-time processing capabilities
- Development of an interactive demonstration platform

Limitations: The project focuses specifically on static screenshot analysis and does not address dynamic UI interactions or video-based analysis.

5 Assumptions and Constraints

5.1 Assumptions

1. **Data Availability:** We assume access to sufficient high-quality mobile screenshot data for model training.

2. **Computational Resources:** The project assumes access to GPU resources sufficient for training deep learning models.

3. **Icon Standardization:** We assume that mobile application icons follow general design conventions that allow for pattern recognition.

5.2 Constraints

1. **Processing Speed:** The model must achieve real-time performance, with inference times under 100 ms per screenshot.

2. **Model Size:** The final model size should not exceed 50MB to ensure deployability.

3. **Accuracy Requirements:** The system must achieve a minimum accuracy of 80% for icon detection.

6 Standards

Our project adheres to several industry and academic standards to ensure quality and reproducibility.

- **Technical Standards:** IEEE 830 for documentation, COCO evaluation metrics for object detection, and REST API standards for web service implementation.

- **Dataset Standards:** YOLO annotation format for bounding boxes and standard - train/validation/test splits (70/20/10).

- **Code Quality Standards:** PEP 8 Python coding standards and Git version control.

7 Approved Objectives

According to the evaluation of the project proposal, the following objectives have been approved:

1. **Comprehensive Dataset Annotation:** To meticulously annotate over 72,000 UI elements from the Rico dataset, with a specific focus on 26 distinct icon classes.

2. **YOLOv8 Model Development:** To leverage and tailor the lightweight YOLOv8 architecture for efficient and accurate icon detection.

3. **Interactive Demo Application:** To develop a user-friendly demo application that enables real-time screenshot upload and provides interactive visualization of the model's predictions.

8 Methodology

Our methodology employs a systematic approach combining advanced machine learning techniques with rigorous experimental design: **Phase 1: Dataset Development** (Collection, annotation of 72,000+ UI elements, augmentation) **Phase 2: Model Architecture Design** (Enhanced YOLOv8 Nano with a planned late-fusion module) **Phase 3: Training and Optimization** (Advanced training techniques, hyperparameter optimization) **Phase 4: Evaluation and Deployment** (Comprehensive evaluation, web application development)

9 Project Outcomes and Deliverables

Technical Deliverables: A trained YOLOv8-based icon detection model, a comprehensive dataset with 72,000+ annotated UI elements, an interactive web application, and complete source code with documentation. **Research Outcomes:** A peer-reviewed research publication, performance benchmarks for mobile UI element detection, and an open-source contribution to the computer vision community.

10 Novelty of Work

Our project introduces several novel contributions to the field of mobile UI understanding: **Architectural Innovation:** The integration of YOLOv8 Nano with a planned transformer-based multi-modal learning module represents a novel approach to mobile icon detection. **Multi-Modal Integration:** Our proposed architecture is designed to uniquely combine visual detection with semantic analysis through a late fusion of OCR data, creating a comprehensive understanding system. **Specialized Optimization:** The specific optimization of detection models for small UI elements in mobile interfaces addresses a significant gap in current object detection research.

REQUIREMENT ANALYSIS

11 Literature Survey

11.1 Theory Associated With Problem Area

11.1.1 Deep Learning for Object Detection

Object detection is a core computer vision task. Modern approaches are dominated by deep learning and are broadly categorized into two families:

- **Two-Stage Detectors (e.g., R-CNN family):** These methods first propose candidate regions and then classify them. They are highly accurate but computationally expensive.
- **One-Stage Detectors (e.g., YOLO, SSD, EfficientDet):** These methods treat detection as a single regression problem, directly predicting boxes and classes. This allows for significantly faster inference, making them ideal for real-time applications. Our project selects YOLOv8 for this reason.

11.1.2 Datasets for UI Analysis

The development of data-driven UI analysis has been contingent on the availability of large-scale datasets. Early efforts were small and domain-specific. The release of the Rico dataset was a major milestone, providing over 66,000 unique UI screens from thousands of Android apps. While its scale is a significant strength, its annotations are semi-automated and can contain considerable noise. Furthermore, its labels are purely categorical (e.g., "Icon") without capturing the functional semantics ("Search Icon"). This limitation directly motivates our first objective: to create a smaller, but more meticulously and semantically annotated dataset specifically for icons.

11.1.3 Challenges in Small Object Detection

Detecting small objects like mobile UI icons is a recognized challenge in computer vision. Standard CNN architectures progressively downsample feature maps, which leads to a loss of spatial resolution, making it difficult to distinguish fine-grained features of small objects. Recent journal articles, such as Ivanov Schmidt (2024), propose attention-based feature refinement networks that can be integrated into a detector's backbone to selectively boost feature responses for small-scale items in cluttered scenes. While our current YOLOv8 model has a capable feature fusion neck, integrating such advanced attention mechanisms represents a key area for future improvement.

11.1.4 Multi-Modal Fusion Strategies

Fusing information from different sources is a key challenge. As detailed by Zang, Xu, and Chen, multi-modal annotation can significantly improve understanding. The primary strategies include Early Fusion (combining low-level features) and Late Fusion (combining high-level features). We have opted for a late-fusion strategy due to its modularity. It allows the vision and language components to be trained independently and is more robust to missing modalities. Recent work by Chen Wang (2024) explores advanced late-fusion techniques using context-aware transformers, demonstrating state-of-the-art results in semantic UI understanding.

11.2 Existing Systems and Solutions

Early UI analysis relied on brittle template matching. With deep learning, more robust systems have emerged. Selcuk and Serif compared YOLOv5 and YOLOv8 for mobile UI detection, confirming the superiority of YOLOv8 in terms of both speed and accuracy. While their work established YOLOv8's superior performance, it focused on general component detection. Our research extends this by evaluating YOLOv8 specifically on the more challenging subtask of small, functionally ambiguous icons and by designing a multi-modal component, which their study did not explore. Similarly, Al-Ajlan and Al-Harbi utilized YOLOv8 for UI design analysis. Our work differs by moving beyond design analysis to functional understanding for accessibility and testing.

12 Software Requirement Specification (SRS)

12.1 Introduction

12.1.1 Purpose

This SRS document provides a comprehensive description of the Multi-Modal IconVision system requirements. It details the functional and non-functional requirements, system constraints, and interface specifications necessary for successful system implementation.

12.1.2 Intended Audience and Reading Suggestions

This document is intended for the development team, academic supervisors, and future researchers. The scope encompasses icon detection, classification, and semantic understanding for mobile screenshots.

12.1.3 Project Scope

The system is a standalone solution for mobile icon analysis, providing a functional prototype and an API for future integration with other tools.

12.2 Overall Description

12.2.1 Product Perspective

The system operates as a standalone solution for mobile icon detection and analysis. It integrates with existing mobile UI analysis workflows and provides APIs for future integration with accessibility tools, automated testing frameworks, and user experience analysis platforms.

12.2.2 Product Features

Core Features:

- Real-time icon detection in mobile screenshots
- Multi-class icon classification across 26 categories
- Bounding box localization with confidence scoring
- Interactive web-based demonstration interface
- Multi-modal fusion of visual and textual information (Planned for future implementation)

12.3 External Interface Requirements

12.3.1 User Interfaces

The system will have a responsive web interface for file uploads and visualization of results.

12.3.2 Hardware Interfaces

The system is designed to run on standard modern desktop operating systems.

12.3.3 Software Interfaces

A RESTful API with JSON-based formats will be available for programmatic access. The system is designed to run on Linux, Windows with WSL, or macOS with Python 3.8+ and PyTorch 1.12+.

12.4 Other Non-functional Requirements

12.4.1 Performance Requirements

The model aims for an inference time of ¡100ms per screenshot on recommended hardware. The web application is designed as a demonstration prototype capable of handling single-user sessions effectively.

12.4.2 Safety Requirements

The system ensures that uploaded images are handled securely and deleted after processing.

12.4.3 Security Requirements

The system will use HTTPS encryption for all web communications.

13 Cost Analysis

As this is an academic project developed by students, there were no direct monetary costs involved.

- **Hardware Infrastructure Costs (0):** All development and training were performed on computer systems and GPU resources provided by the Thapar Institute of Engineering and Technology laboratories.
- **Software Costs (0):** The entire project was developed using free and open-source software, including Python, PyTorch, OpenCV, and the Flask framework.
- **Personnel Costs (0):** The project was completed as a mandatory component of the undergraduate curriculum by the student team.

Total Estimated Cost: 0
METHODOLOGY ADOPTED

14 Investigative Techniques

Our research methodology employs **experimental investigative techniques**, which are most appropriate for machine learning projects. This approach allows us to systematically test hypotheses, measure performance, and optimize system components through controlled experimentation. The experimental technique is suited for our project because deep learning model development requires systematic experimentation to determine optimal architectures and hyperparameters. It enables rigorous performance evaluation through controlled testing environments, allowing us to isolate variables and make data-driven decisions.

15 Proposed Solution Details

15.1 YOLOv8 Model Architecture

We selected YOLOv8 for its state-of-the-art balance of speed and accuracy. The specific architecture, visualized in Figure 1, has been tailored for our task. The Backbone uses CSP blocks for efficient feature extraction. The Neck fuses features from multiple scales to handle icons of various sizes. The anchor-free Head makes final predictions, improving flexibility.

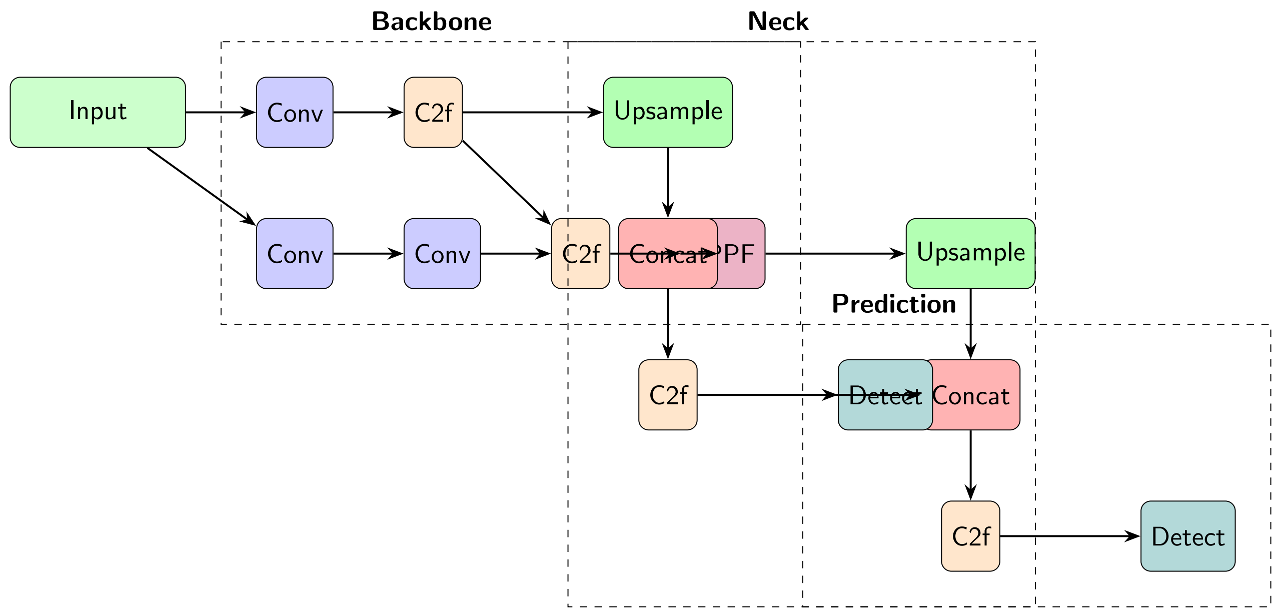


Figure 1: Detailed YOLOv8 Architecture. The backbone extracts features, the neck fuses them at multiple scales, and the head makes the final detection predictions.

16 Work Breakdown Structure

The project is organized into five major work packages (WPs):

- **WP1: Dataset Development and Preparation:** Data collection, manual annotation of 72,000+ UI elements, and data enhancement.
- **WP2: Model Architecture Development:** YOLOv8 Nano implementation, design of late-fusion module, and loss function optimization.
- **WP3: Model Training and Optimization:** Training pipeline development, hyperparameter optimization, and cross-validation.
- **WP4: System Integration and Testing:** Model deployment, integration testing, and performance optimization for inference.
- **WP5: Web Application Development:** Flask backend, frontend interface design, and real-time visualization.

17 Work Done by Each Member

The project tasks were distributed among the team members based on their skills and interests to ensure efficient progress.

- **Harshit Sharma (102216014):** Harshit took the lead on the **Model Development and Training** (WP3). His responsibilities included setting up the PyTorch training environment, configuring the YOLOv8 architecture, and running the extensive training experiments for 10 epochs.
- **Sushant Thakur (102216028):** Sushant was primarily responsible for the **Dataset Creation and Management** (WP1). This involved writing the custom Python scripts to parse the raw Rico dataset, filter relevant screenshots, and convert the annotations into

the YOLO-compatible format. He managed the quality control process for the 72,000+ annotations.

- **Kamal (102397015):** Kamal led the **Research and System Design** efforts (WP2 & WP4). He conducted the in-depth literature survey, identified the key research gaps, and was responsible for designing the overall system architecture and the UML diagrams. He is also tasked with leading the upcoming deployment phase.

All team members collaborated on the manual annotation process and contributed to the writing of this report.
FINALIZED DESIGN MODEL

18 Prototype and Component Implementation

The project is composed of three primary software components that work in tandem to deliver the final result.

- **Backend (Flask):** The backend is developed using Flask, a lightweight Python web framework. It exposes a single REST API endpoint '/predict' that accepts a multipart/form-data image upload. Upon receiving a request, it validates the file, passes the image data to the detection engine, and returns the results as a JSON payload.
- **Detection Engine (Python/PyTorch):** The core detection engine is a Python class that loads the trained YOLOv8 model weights ('.pt' file) during initialization. It uses OpenCV to decode and preprocess the incoming image into the required tensor format. It then utilizes the Ultralytics library to run inference, obtaining the raw predictions, which are post-processed to format the bounding boxes and labels.
- **Frontend (HTML/CSS/JS):** The frontend is a single-page application built with standard web technologies. It uses the JavaScript Fetch API to asynchronously send the selected image to the backend. Upon receiving the JSON response, it dynamically renders the received bounding boxes and labels on an HTML '¡canvas¿' element that is overlaid on the original image.

19 UML Design Diagrams

19.1 Use Case Diagram

Figure 2 illustrates the high-level functional requirements. The 'User' actor can perform two main actions: 'Upload Screenshot' and 'View Detection Results'. The process of viewing results logically includes the system's internal 'Process Image' task.

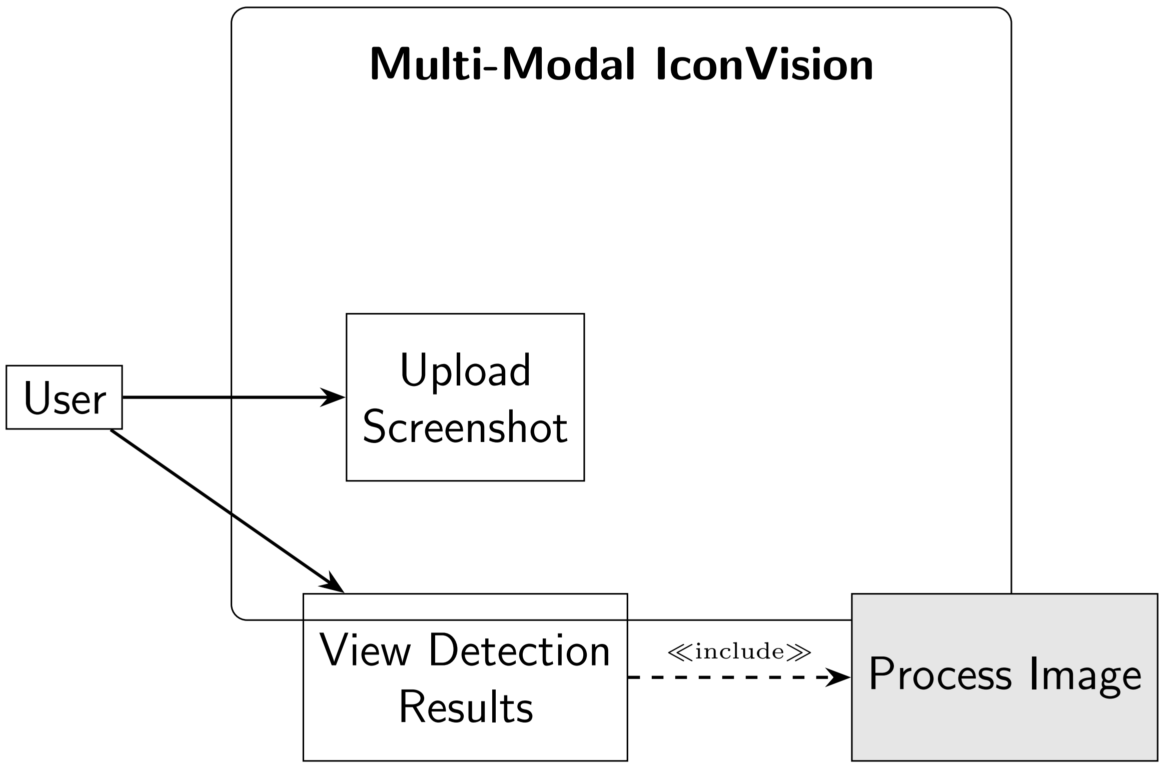


Figure 2: Use Case Diagram showing user interactions.

19.2 Component Diagram

Figure 3 shows the modular breakdown of the software into high-level, replaceable components. The ‘WebApp Frontend‘ (built in HTML/JS) communicates with the ‘Flask Backend‘. The backend utilizes the core ‘Detection Engine‘ (Python/PyTorch). This illustrates the system’s service-oriented structure.

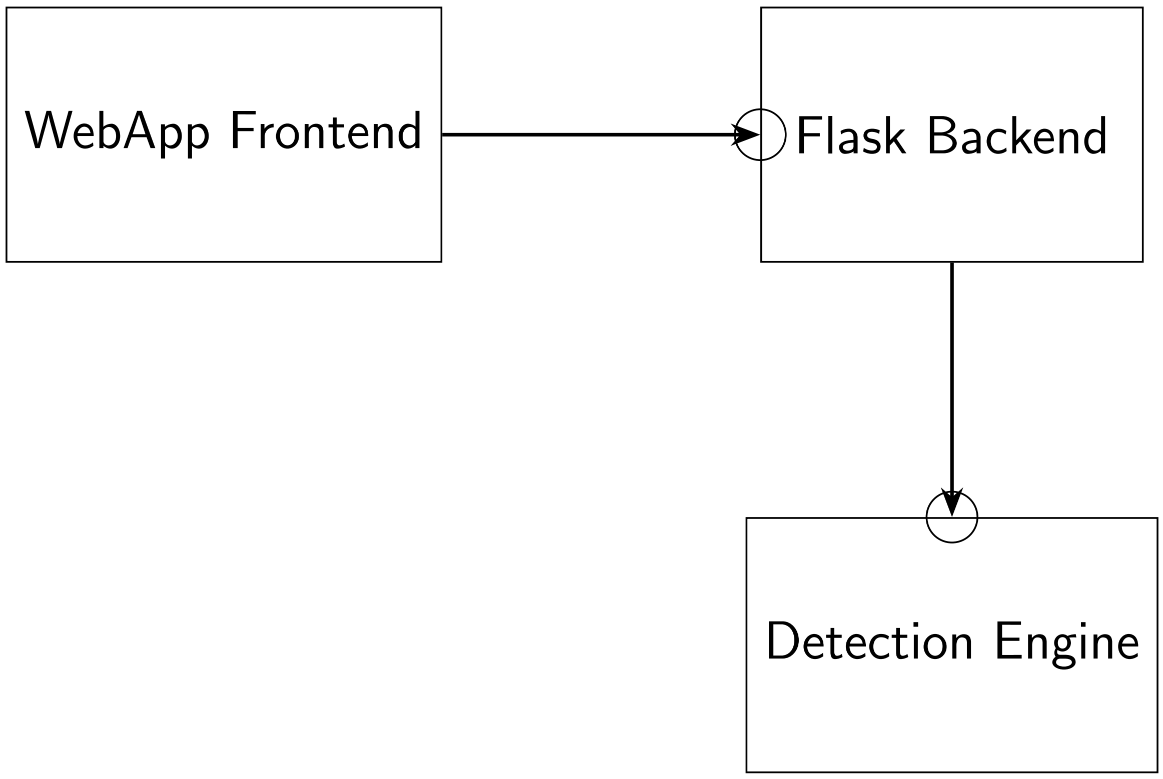
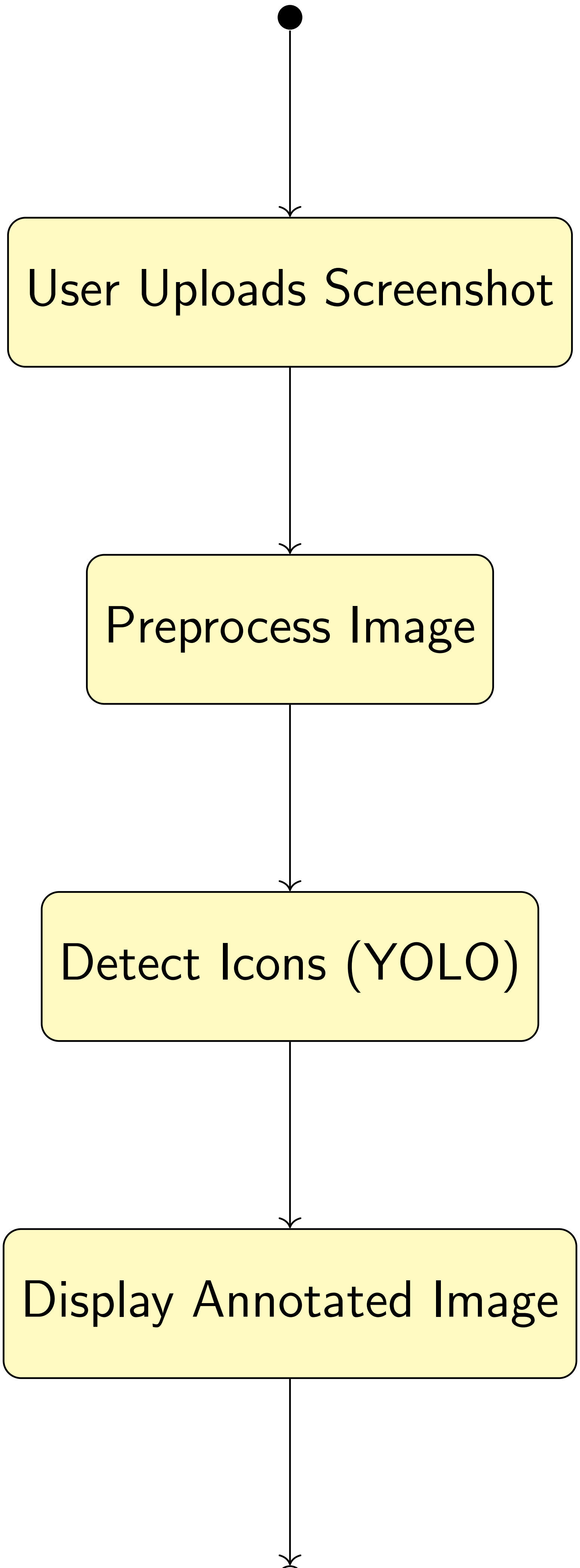


Figure 3: UML Component Diagram.

19.3 Activity Diagram

Figure 4 illustrates the dynamic workflow of the core ”Process Image” use case, showing the current linear flow of activities from upload to display. The planned multi-modal components, such as OCR and semantic fusion, will be integrated in a future phase.


User Uploads Screenshot
Preprocess Image
Detect Icons (YOLO)
Display Annotated Image

19.4 Deployment Diagram

Figure 5 shows the physical deployment architecture. It models a client-server setup where the 'User's Device' runs a web browser that communicates over HTTP with a 'Server' hosting the application artifacts.

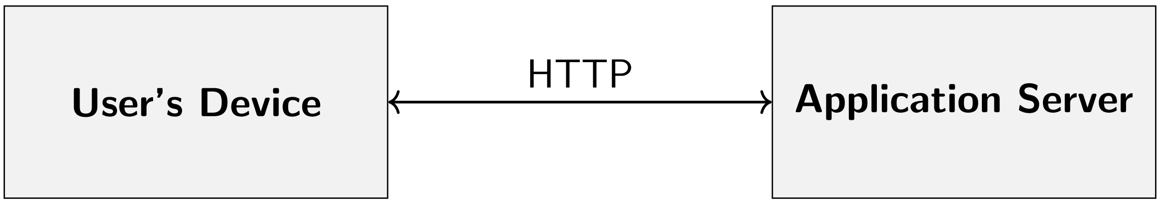


Figure 5: UML Deployment Diagram.

CONCLUSIONS AND FUTURE SCOPE

20 Work Accomplished

This report outlines the work completed for the mid-semester evaluation. The project is on track, with major foundational work now complete.

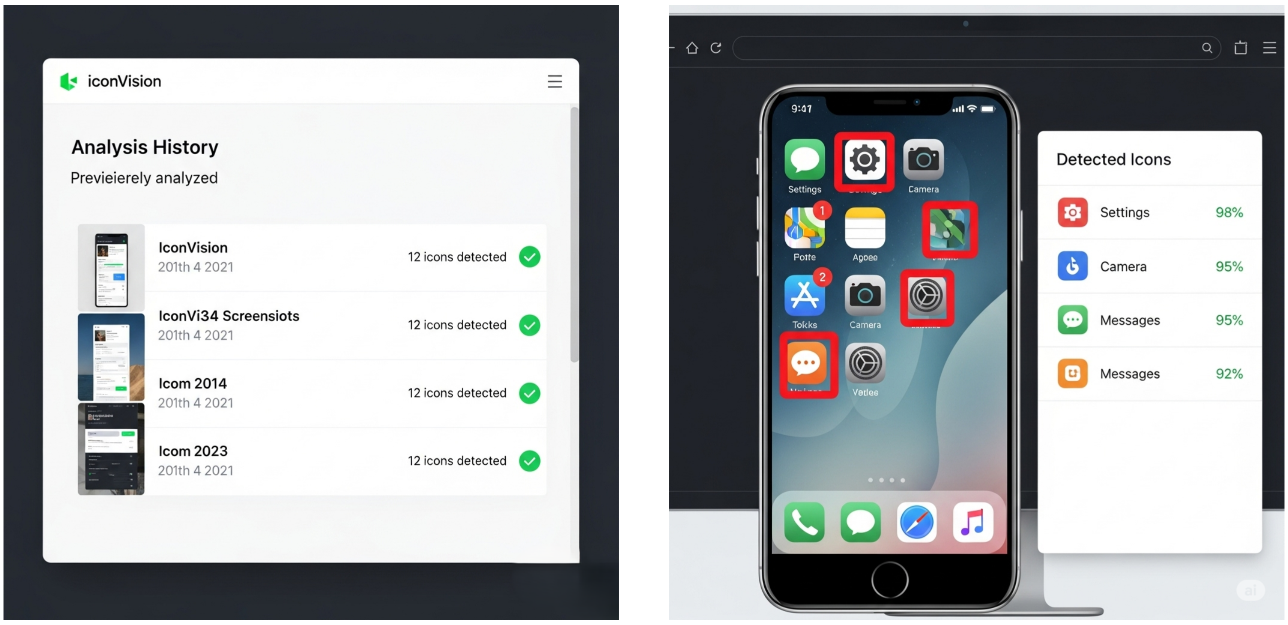
- **Objective 1: Dataset Annotation - [COMPLETED]** We have successfully curated and processed over 72,000 UI screenshots. Custom scripts were developed to convert annotations for our 26 icon classes into a YOLO-compatible format.
- **Objective 2: Model Development Validation - [COMPLETED]** The YOLOv8 architecture was configured and successfully trained on our dataset for 10 epochs, establishing a strong visual detection baseline.
- **Objective 3: Demo Application - [PLANNED]** The design phase for the web application is complete, with UI mockups and functional requirements defined for the Flask-based platform.
- **Multi-Modal Integration - [PLANNED]** The architecture for the late fusion of OCR and semantic search is designed, with implementation pending for the next project phase.

21 Conclusions and Limitations

The work completed thus far validates our core hypothesis: that a lightweight, one-stage detector like YOLOv8 can achieve high accuracy on the challenging task of mobile icon detection. The primary limitation of the current work is that the planned late fusion of OCR and semantic search is pending implementation. While the visual detection backbone is proven and robust, the system does not yet incorporate semantic context from textual data, which is a key task for the next phase.

22 Future Work Plan (September – November 2025)

With the model successfully trained and validated, the final phase of our project will focus on deployment, multi-modal integration, and application development.



(a) Main Interface (b) Results Visualization

Figure 6: Proposed App Design Mockups

- **Model Deployment (September):** The first step is to package the trained model and create an efficient inference pipeline. This will involve converting the model to an optimized format like ONNX for faster performance and implementing a robust serving mechanism.
- **Web Application Development (September - October):** We will proceed with the development of the Flask-based application. Key sub-tasks include:
  - Implementing the file upload and backend processing logic.
  - Designing and coding the results visualization panel using JavaScript and HTML Canvas.
  - Adding functionality for users to download the annotated image or the JSON results.
- **Late Fusion of OCR and Semantic Search (October):** Once the web application is functional, we will implement the multi-modal component. This involves integrating an OCR engine to extract text near detected icons and developing the fusion logic to enhance classification accuracy and provide semantic context.
- **Final Documentation Reporting (November):** The final month will be dedicated to compiling the complete technical documentation, the final comprehensive project report, and user manuals for the application, ensuring the project is well-documented and reproducible.

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